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Multi-Objective Optimization of Metal Parameters for Surface Roughness and Response Analysis

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ABSTRACT:- *In manufacturing sector the Surface grinding process is used to produce smooth finish on flat metal surface. The rate of metal removal and Surface quality are the two important performance characteristics to be considered in the grinding process. The economics of the machining process is affected by several factors such as abrasive wheel grade, wheel speed, depth of cut, table speed and material properties. In this research paper, an empirical model is developed by considering the control factors like wheel speed, table speed and depth of cut using response surface methodology for surface roughness and rate of metal removal. Response surface methodology (RSM) has been applied to determine the optimum machining parameters leading to minimum surface roughness and maximum metal removal rate in Surface grinding process operation on EN24 steel. The second order mathematical models in terms of machining parameters had been developed for metal removal rate (MRR) and Surface roughness on the basis of experimental results. The model has been selected for optimization that has been validated with F-test. The adequacy of the models is tested by using analysis of variance (ANNOVA). An attempt has also been made to optimize cutting parameters using multi-objective characteristics for the developed prediction models using Response surface methodology (RSM).*

KEYWORDS: *Surface grinding, MRR, Surface roughness, RSM, Optimization.*

I. INTRODUCTION

Surface roughness measurements are essential in characterization of the features of a machined surface. To examine the effect of cutting parameters on surface roughness thoroughly, a huge number of experiments are needed, depending on the number of parameters. By utilizing the method of design of experiments (DoE), the number of experiments can be reduced in such a way that the effect of parameters could be assessed appropriately. If linear effects of cutting parameters are considered, then fractional factorial design is sufficient, but to examine the quadratic term, RSM method has to be utilized.

Machining industries continuously demanding for higher production rate and improved machine ability as quality and productivity play a significant role in today's manufacturing market. The extent of quality of the procured item (or product) influences the degree of satisfaction of the consumers during the usage of the procured goods. Higher production rate can be achieved at high cutting speed, feed, depth of cut which is limited by tool wear, capability of tooling, surface finish and accuracy required selection of cutting parameters is generally a compromise between several variables and it can be easily possible to determine by using Response Surface Methodology.

Harsimran Singh Sodhi and Dhiraj Prakash Dhiman et al [2] have illustrated the role of Taguchi parameter optimization methodology for optimize cutting parameters in boring. The results of analysis show that feed rate and cutting speeds have present significant contribution on the surface roughness. Yogendra Tyagi and Vedansh Chaturvedi et al [3] have illustrated optimal machining parameters i.e., spindle speed, depth of cut and feed rate) for drilling machine operations have been investigated in order to minimize the surface roughness. Turgay Kıvak and Gurcan Samtas et al [4] have been investigated that optimization of drilling parameters using the Taguchi technique to obtain minimum surface roughness (Ra). Ajeet Kumar rai and Shalini yadav et al [6] have applied Taguchi method to study the performance characteristics of machining parameters (cutting speed, feed rate and depth of cut) with consideration of surface finish.

Current investigation on boring process is a Response Surface Methodology applied on the most effective process parameters i.e. feed, cutting speed and cutting allowance while machining Gray cast iron of work pieces with Carbide cutting tool in dry condition. The main effects (independent parameters), quadratic effects (square of the independent variables), and interaction effects of the variables have been considered separately to build best subset of the model. Three levels of the feed, three levels of speed, and two level of cutting allowance have been used. After having the data from the experiments, the performance measures surface roughness (Ra) of Engine crankcase bore has taken by Mitutoyo Surface Roughness Tester. To analyze the data set, statistical tool DESIGN EXPERT-9 (Software) has been used to reduce the manipulation and help to arrive at proper improvement plan of the Manufacturing process & Techniques. Hypothesis testing has been done to check the goodness of fit of the data. A comparison between the observed and predicted data have been made, which shows a close relationship. The experimentation plan is designed using design of experiment, 18 experiments and Design Expert 9.0 statistical software is used. Optimal values of process parameters for desired performance characteristics are obtained by analysis of variance (ANOVA). This paper is categorized as six sections. The first section is the introduction. The second section is related work. The third section is the response surface methodology and followed by results and discussions ends with conclusion.

II. RELATED WORKS

Extensive study, analysis and research work has been done in the field of EDM. The basic of EDM can be traced as far as back 1907, when English chemist Joseph Priestly discovered the erosive effect of sparks (Singh and Bhardwaj, 2011). Since then a lot of work has been done in this field, various theories have been put to explain the process thoroughly, but mechanism of EDM is still arguable. Rebelo et al. (2000) studied the electro discharge machining of copper-beryllium alloy and reported that Surface roughness increases with both increase of discharge current and pulse on-time. Lee et al. (2001) studied the machining characteristics (MRR, SR and Electrode wear rate) of electro-discharge machining of tungsten carbide and found that the optimum conditions for low TWR and surface roughness were gap voltage of 120V), discharge current of 24A, pulse duration of 12.8µs, pulse interval of 100 µs dielectric flushing pressure of 50Kpa, CuW as the tool electrode material with negative polarity. Tzeng et al. (2001) studied the effects of various powder characteristics (aluminium, chromium, copper, and silicon carbide) on the efficiency in electro-discharge machining of SKD-11 alloy. It is resulted that the particle size, the particle concentration, the particle density, the electrical resistivity and the thermal conductivity are significant factors affecting the EDM performance. Guu et al. (2003) studied the surface morphology, surface roughness and micro-cracking in the electrical discharge machining of AISI D2 tool steel. The investigating parameters were pulsed current 0.5, 1.0, 1.5 Amp, Pulse-on duration 3.2, 6.4 µs pulse-off duration 20 µs, and reported that the higher pulsed current and higher pulse-on duration cause a poorer surface finish. Shabgard,et al. (2009) presented an experimental investigation to consider the machining characteristics in EDM process of FW4 welded steel and reported that the regression technique is an important tool for representing the relation between machining characteristic and EDM process input parameters, and the obtained mathematical models indicating the correlation perfectly.

III. RESPONSE SURFACE METHODOLOGY

RSM is the collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize the response. In response Surface Methodology (RSM) the factors that are considered as most important are used to build a polynomial model in which the important variable is the experiment' Response. In order to know the surface quality and dimensional properties in advance, it is necessary to employ theoretical models, making it feasible to do prediction of operating conditions

In many engineering fields, there is a relationship between output variables 'y' of interest and a set of controllable input variables{x1, x2, … , xn}. In some system, the nature of the relationship between y and x values may be known. Then, a model can be written in the form

$y = f(x1, x2, \ldots , xn) + s,$

where s represents error observed in the response y. If we denote the expected response as,

$E(y) = f(x1, x2, \ldots , xn) = \hat{y}$

then the surface represented by

$\hat{y} = f(x1, x2, \ldots, xn)$

In most of the RSM problems, the form of the relationship between the response and the independent variable is unknown. Thus the first step in RSM is to find out a suitable approximation for the true functional relationship between y and set of independent variables employed. Usually a second order model is utilized in RSM .The þ coefficient used in the model below can be calculated by means of least square method.

3.1 MATHEMATICAL FORMULATION

The first order and second order Mathematical models were developed using multiple regression analysis for both the output responses namely surface roughness and metal removal rate. Multiple regression analysis [17-22] is a statistical technique, practical, easy to use and accurate. The aim of developing the mathematical models is to relate the output responses with the input machining parameters and there by optimization of the machining process. By using these models, optimization problem can be solved by using Taughis optimization procedure as multi objective function model.

The mathematical models can be represented by

Y= f (V,N,d)

Where Y is the output grinding response, V, N, d are the table speed, wheel speed, depth of cut respectively
To determine the above constants and exponents, this mathematical model have to be linearisied by performing the logarithmic transformation which as follows

$\ln MRR = \ln k_1 + a_1 \ln V + b_1 \ln N + c_1 \ln d$

$\ln R_a = \ln k_2 + a_2 \ln V + b_2 \ln N + c_2 \ln d$

The constant and exponents can be determined by the method of least squares. The first order and second order linear models, develop from the above functional relationship using the least square regression analysis can be represented as follows

$Y_1 = Y - e = b_0x_0 + b_1x_1 + b_2x_2 + b_3x_3$

Where Y_1 is first order output response of metal removal rate, Y is the measured metal removal rate, x1x2x3 are the logarithmic transformations of table speed, wheel speed, depth of cut, respectively. The second order polynomial of output response will be given as

$Y_2 = Y - e = b_0x_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_{12}x_1x_2 + b_{13}x_1x_3 + b_{23}x_2x_3 + b_{11}x_1^2 + b_{22}x_2^2 + b_{33}x_3^2$

Where Y_2 is second order output response of metal removal rate Y is the measured metal removal rate, b_0, b_1, b_2, b_3, b_{12}, b_{13}, b_{23}, b_{11}, b_{22} b_{33} are estimated by the method of lest squares. The validity of this mathematical model will be tested using F test, Chi-Square test before going for optimization.

IV. RESULTS & DISCUSSION

As mentioned earlier, Design Expert software was used to analyze the results obtained in order to identify the significant factors and interactions between the factors under studied. Analysis of variance (ANOVA) table is commonly used to summarize the experimental results. These tables conclude information of analysis of variance and case statistics for further interpretation. In this section, all the analysis was presented in normal probability plot, main effect plot and interaction plot for the dependent parameters that significant to the responses.

4.1 ANALYSIS RESULTS FOR SURFACE ROUGHNESS (RA)

Surface roughness (Ra) in tappet bore processes is an important factor because it is main part of engine crankcase. Table 1 indicates the final analysis of ANOVA for Surface roughness (Ra).

Table 1: Sequential Model Sum of Squares

Source	*Sum of Square*	*df*	*Mean Square*	*F-Value*	*Desirability*
Mean vs Total	305.29	1	305.29		
Linear vs	9.02	3	3.01	17.72	Suggested
2FI vs Linear	0.10	3	0.035	0.17	
Quadratic vs 2FI	2.14	2	1.07	71.29	Aliased
Residual	0.13	9	0.015		
Total	316.68	18	17.59		

4.1.1. Main effects plot for Ra

Regression analysis equation for Ra value:- The results obtained by this method has formed as regression analysis equation for Ra Value equation by the same software and given as equations.

4.1.2 Final Equation in Terms of Coded Factors:

Surface Roughness (Ra) = +4.12+0.13*A-0.85*B-0.068*C

4.1.3 Final Equation in Terms of Actual Factors:

Surface Roughness (Ra) = +9.69611+1.27222*CA- 0.042500*CS-0.68333*FR

The formed equation has been validated by the tests. Moreover the formed equation of Regression Analysis have been also plotted as Diagnostic Plots between actual and predicted values of response. The graph between actual and predicted values is shown in Figure 3.1. The plot shows scattered points a little bit deviated from fitted line. The low range values of Surface roughness are shown in blue color points and high range values in red color. It indicates that lowest value of Ra i.e. 2.61(blue) and the value 4.9 (red) are most deviated experimental values.

Main Effect Graph between cutting allowance and Ra Value interprets that at the minimum value of cutting speed and feed rate has been increased value of Ra, if cutting allowance is increased from minimum to maximum value. At maximum value of cutting speed and minimum feed rate, it has been predicted increased value of Ra if cutting allowance is increased from its minimum to maximum value. At maximum value of cutting speed and maximum feed it predicted the increased value of Ra by increasing cutting allowance from its minimum to maximum value. Whereas at minimum value of cutting speed and maximum feed, it predicts the increased value of Ra by increasing cutting allowance from its minimum to maximum value.

4.2 Main effect of spindle speed on surface roughness

Figure a represents the main effect of spindle speed on surface roughness. From Fig.4.2 , it can be observed that the surface roughness decreases as the spindle speed is increased from 500 to 1000 rpm. At higher spindle speed, BUE formation tendency is decreased, more heat is carried away by the chip and less heat is dissipated to the workpiece. Hence, the surface roughness is decreased. The spindle speed should be kept at high level (1000 rpm) to achieve minimum surface roughness.

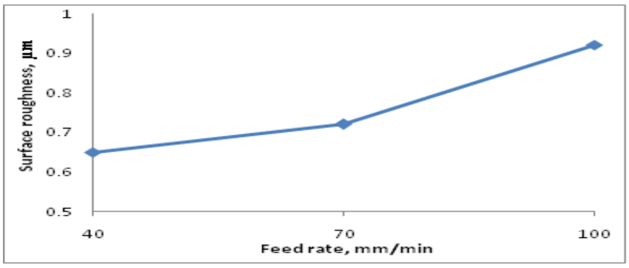

Fig: 4.2 Spindle speed on surface roughness

4.2.1 Main effect of feed rate on surface roughness

Figure 4.2.1 represents the main effect of feed rate on surface roughness. From Fig. 4.2.1, it is observed that surface roughness decreases with decrease in feed rate. Hence, the feed rate should be kept at low level (40 mm/min) to achieve better surface finish. Increase in feed rate increases the area of contact between tool and work piece. It increases the cutting forces and promotes higher values of surface roughness on the work piece surface.

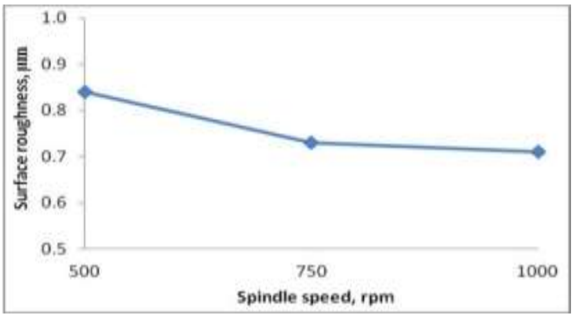

Fig: 4.2.1 Feed Rate on Surface roughness

4.2.2. Main effect of axial depth of cut on surface roughness

Figure c represents the main effect of axial depth of cut on surface roughness. From Fig. 7, it is observed that the surface roughness increases as the axial depth of cut is increased from 0.4 mm to 1.2 mm. The increase in depth of cut increases chip cross- sectional area and volume of material removal. Due to these cutting force and chatter are increased. Hence, the surface roughness is increased. The depth of cut should be kept at low level (0.4 mm) to achieve minimum surface roughness.

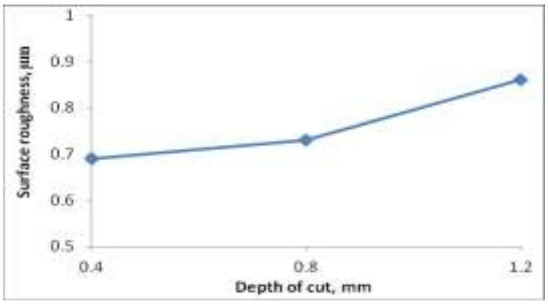

Fig: 4.2.2 Main Effect of Depth of Cut on Surface Roughness, *Ra*.

The optimum results for the output responses namely surface roughness and Metal removal rate in terms of machining parameters namely wheel speed, table speed and depth of cut on EN 24 steel on CNC surface grinding machine. The confirmation experiment was conducted and there is a good agreement between predicted and experimental values.

5.1 Output Fault Analysis:

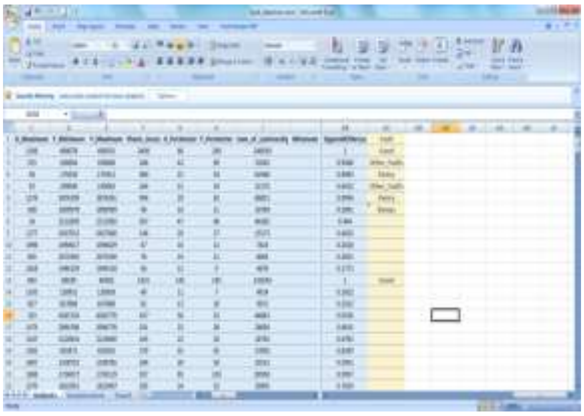

Fig 5.1 Output Fault Analysis

It is found that the error in predicted and experimental values. It is found that the error in prediction of the optimum conditions is about 3 to 8%. Thus, the response optimization predicts the optimum conditions fairly well.

5.2 Plate Velocity:

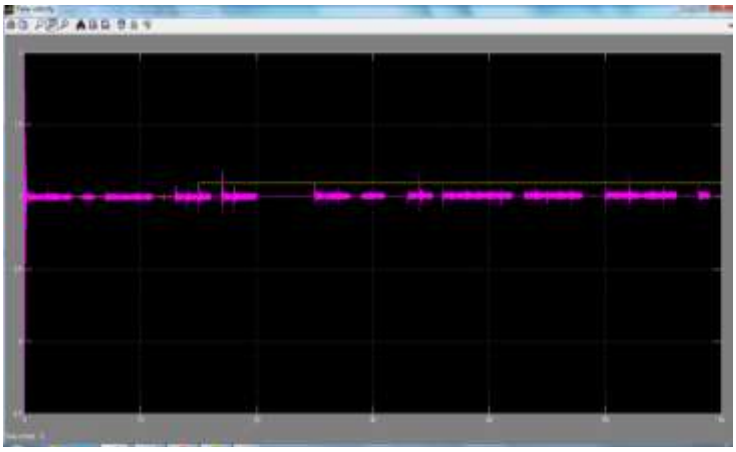

Fig 5.2 Plate Velocity

5.3 Plate Thickness:

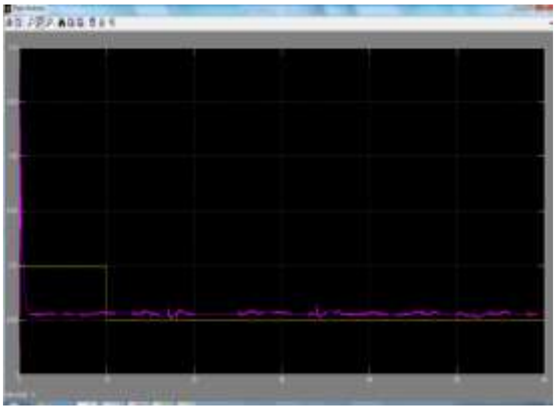

Fig: 5.3 Plate Thicknesses

5.4 Force:

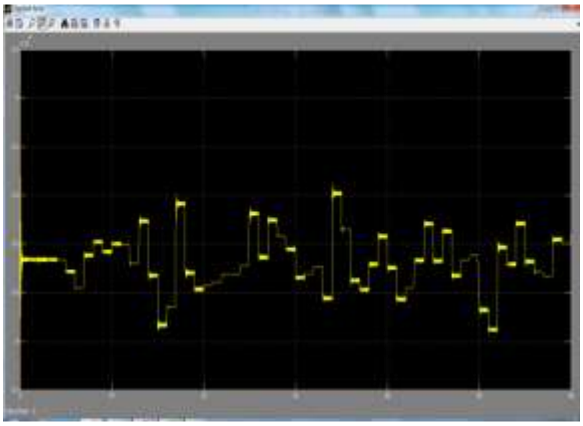

Fig: 5.4 Force

VI. CONCLUSIONS

In this study, an experimental investigation performed to evaluate the surface roughness and MRR parameters of EN 24 steel in surface grinding operation has been presented. A plan of experiments has been prepared in order to test the influence of cutting speed, feed rate and depth of cut on the output parameters. The obtained data have been statistically processed using response surface method. The empirical models of output parameters are established and tested through the analysis of variance to validate the adequacy of the models. It is found that the surface roughness and MRR parameters greatly depend on work piece materials. A response surface optimization is attempted using Mat Lab software for output responses in surface grinding.

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