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Parametric Analysis of EN 353 Alloy Using MQL Machining with Response Surface Method

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Abstract — Heat generated in any conventional machining between tool and work- piece can be minimized by the use of cutting fluids since the latter plays a vital role in terms of improving surface quality and its characteristics because of its properties like continuous lubrication, cooling and chips flushing etc. As extensive use of cutting fluids increase the machining costs, the problem can be overcome by employing a sustainable manufacturing technique known as Minimum Quantity Lubrication (MQL) which reduces the flow of cutting fluid. On the other hand researches are focusing on Nano based fluids which are gaining more importance. As nano based cutting fluids are colloidal mixture of nano sized particles and a base fluid, which enhance the heat transfer characteristics suitable for machining applications. The present paper focuses on the application of Hybrid Nano based cutting fluids for machining of alloy steel under different MQL flow conditions. Using response surface methodology (RSM), an optimum solution is obtained for the selected input parameters to the output response-surface roughness. A regression relation is developed between the input and output responses with the help of Response surface methodology (RSM).

Keywords — Minimum Quantity Lubrication, Response Surface Methodology, Hybrid Nano Based Fluids, Surface Roughness etc.

I. Introduction

In the recent advancements, Nano based fluids are being used as a viable alternate cutting fluid in any machining operations, where considerable improvement in the performance characteristics was observed [1-3]. Now a day’s researchers are focusing on hybrid nano fluid compared to single nano cutting fluids, where two or more different nano particles are mixed with base fluid [4]. On the other hand, Researchers are also focusing on the implementation of Sustainable manufacturing techniques (one of the recent trends in current industrial sector) like Minimum Quantity Lubrication as it is eco-friendly, cost effective, waste free and energy efficient technique. Several researches [5-11] have been carried out through MQL technique where as in the present paper an attempt is made in order to study the machining characteristics of MQL using hybid nano fluid for different flow rates i.e. at 100ml/hr, 200ml/hr and 300ml/hr, RSM [12-17] is used to develop, optimize and improve the process in order to minimize the surface roughness for the variables i.e. MQL flow rate, speed, feed and depth of cut

II. Materials and Method

The experimentation is carried out using RSM method, which involves with the experimental situations where four independent variables i.e. MQL flow rate (A), speed (B), feed (C) and depth of cut (D) which potentially impact response variable i.e. surface roughness. To study the responses effect Box-Behnken experiment design at three different levels is adopted using Minitab software. The factors and their levels are shown in the Table 1.

Table 1: Input Variables

VARIABLES	UNITS	(-1) LOW	(0) CENTRE	(+1) HIGH
MQL-FLOW RATE (A)	ML/HR	100	200	300
SPEED (B)	RPM	700	1100	1500
FEED (C)	MM/REV	0.2	0.5	0.8

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DEPTH OF CUT (D)	MM	0.5	1.5	2.5

The experiments were carried out using LOKESH TL20 Max Model CNC machine shown in fig. 1. The MQL setup was developed using three different "Spray gun" maintaining the flow rate of 100 ml/hr, 200 ml/hr and 300 ml/hr with an air compressor maintaining an air pressure of 2 bars shown in fig. 2. The cutting tool used is TNMG uncoated carbide tool. The work piece material used is EN 353 Alloy steel of 32mm diameter X 150mmlength shown in fig. 3. The coolant hybrid nano based fluid is prepared by probe sonicator ultrasonic device with 0.75 % -Al2O3 and 0.25 % -Cu weight of nano sized particles and distilled water as base fluids with stabilizers is mixed thoroughly and maintained shown in fig.no.5. The Box-Behnken design is developed considering the input variables and tabulated in table no.2, 27 experiments were performed as per the standard order design sequence and the corresponding surface roughness is measured tabulated in table no. 2

Fig.1 CNC machine

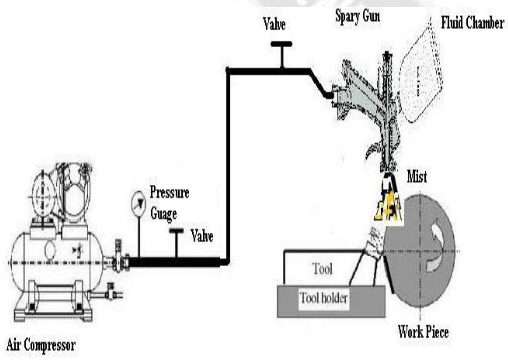

Fig. 2 Layout of MQL setup

Fig.3 EN 353 Alloy

Fig. 4 Al_2O_3Nano particles

Fig.5 Cutting Fluid

Fig.6 Surface Roughness measuring device

III.RESULTS AND DISCUSSION

Table 2: Box-Behnken Design Experimentation with Roughness Values

MQL-FR (A)	SPEED (B)	FEED (C)	DEPTH OF CUT (D)	SURFACE ROUGHNESS (Ra)
100	1100	0.8	1.5	2.63
100	1100	0.2	1.5	2.23
200	1100	0.5	1.5	2.55
100	700	0.5	1.5	2.89
300	1100	0.5	0.5	1.42
100	1500	0.5	1.5	2.45
300	1100	0.8	1.5	2.09

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200	1100	0.2	2.5	1.99
200	1500	0.5	0.5	1.48
300	700	0.5	1.5	2.01
300	1100	0.5	2.5	1.74
300	1500	0.5	1.5	1.62
200	700	0.5	0.5	2.34
200	1100	0.8	2.5	2.36
200	1100	0.2	0.5	1.86
200	700	0.2	1.5	2.24
100	1100	0.5	2.5	2.82
200	1500	0.5	2.5	2.43
200	1500	0.2	1.5	2.01
300	1100	0.2	1.5	1.74
200	1100	0.5	1.5	1.92
200	700	0.8	1.5	2.36
100	1100	0.5	0.5	2.01
200	1100	0.5	1.5	2.06
200	700	0.5	2.5	2.54
200	1500	0.8	1.5	2.12
200	1100	0.8	0.5	2.2

In RSM, the experimental design and regression equation helps in retrieving the response for selected independent input variables [13-17] with the equation below

X=b0 + b1Y1 +b2Y2 +b3Y3+…………. + bnYn+e --------- Eq.1

Where,X is output response, Y1,Y2….. are input factors and its corresponding interactions, and b1,b2….. are the quadratic model associated with regression of RSM.

Based on the experimental design the surface roughness measured and tabulated in table 2, the quadratic equation developed by calculating coefficient of regression for surface roughness is given by eq.2 [17].

(R_a)Surface Roughness =2.177 - 0.3675 MQL flow rate - 0.1892 SPEED + 0.1408 FEED + 0.2142 DOC - 0.0313 MQL flow rate * MQL flow rate + 0.0738 SPEED * SPEED - 0.0087 FEED * FEED - 0.0888 DOC * DOC + 0.013 MQL flow rate * SPEED - 0.013 MQL flow rate * FEED - 0.123 MQL flow rate * DOC - 0.002 SPEED * FEED + 0.188 SPEED * DOC + 0.007 FEED * DOC -------------Eq. 2

Table 3: ANOVA table of RSM for Ra

	DF	Adj SS	Adj MS	F-Value	P-Value
Model	14	3.1515	0.2251	5.1	0.004
Linear	4	2.8385	0.7096	16.07	0.000
MQL flow rate	1	1.6206	1.6206	36.7	0.000
SPEED	1	0.42941	0.4294	9.72	0.009
FEED	1	0.23801	0.2380	5.39	0.039
DOC	1	0.55041	0.5504	12.46	0.004
Square	4	0.11092	0.0277	0.63	0.652
MQL flow rate*MQL flow rate	1	0.00521	0.0052	0.12	0.737
SPEED*SPEED	1	0.02901	0.0290	0.66	0.433
FEED*FEED	1	0.00041	0.0004	0.01	0.925
DOC*DOC	1	0.04201	0.0421	0.95	0.349
2-Way Interaction	6	0.20215	0.0336	0.76	0.613
MQL flow rate*SPEED	1	0.00063	0.0006	0.01	0.907
MQL flow rate*FEED	1	0.00063	0.0006	0.01	0.907
MQL flow rate*DOC	1	0.06003	0.0600	1.36	0.266
SPEED*FEED	1	0.00002	0.0002	0	0.981
SPEED*DOC	1	0.14063	0.1406	3.18	0.1
FEED*DOC	1	0.00022	0.0002	0.01	0.944
Error	12	0.5299	0.0441		
Lack-of-Fit	10	0.31103	0.0311	0.28	0.93
Pure Error	2	0.21887	0.1094		
Total	26	3.68147			

Where Ra is the output response dependent variable and MQL flow rate, Speed, Feed, Depth of cut are the input variables which are independent measures. The ANOVA is performed and tabulated in table 3, in order to define the significance of the input parameters towards the output variable and to check the model adequacy. From ANOVA table no. 3; the F- model calculated is 5.1 which indicates the model is significant as the F-tabulated value at a confidence level of 95% measured to be 4.26 i.e. $F_{cal} > F_{tab}$. The value of P < 0.0500 implies a model term is significant. In this case MQL flow rate, Speed, Feed, Depth of cut are said to be significant model terms. The value > 0.1 indicate the model is not significant. The lack of fit is 0.93 which indicates it's not significant, as lack of fit with Non-significant is good –as it is needed that the model is to be fit [15-17]. Model showed a coefficient correlation (R2) of 85.61 % value suggesting a good representation of model and satisfactory correlation between theoretical and experimental values provided by the model equation.

Furthermore the insignificant terms are eliminated using an approach of backward elimination in order to fit the full model, hence the regression equation considering second order terms is given by Eq.3.

Ra = 2.851 - 0.003675 MQL flow rate - 0.000473 SPEED + 0.469 FEED + 0.2142 DOC ------------- Eq. 3

Table 4: ANOVA table of RSM for modified Ra

	DF	Adj SS	Adj MS	F-Value	P-Value
Model	4	2.8385	0.70963	18.52	0.000
Linear	4	2.8385	0.70963	18.52	0.000
MQL flow rate	1	1.6207	1.62067	42.3	0.000
SPEED	1	0.4294	0.42941	11.21	0.003
FEED	1	0.238	0.23801	6.21	0.021
DOC	1	0.5504	0.55041	14.36	0.001
Error	22	0.843	0.03832		
Lack-of-Fit	20	0.6241	0.03121	0.29	0.951
Pure Error	2	0.2189	0.10943		
Total	26	3.6815			

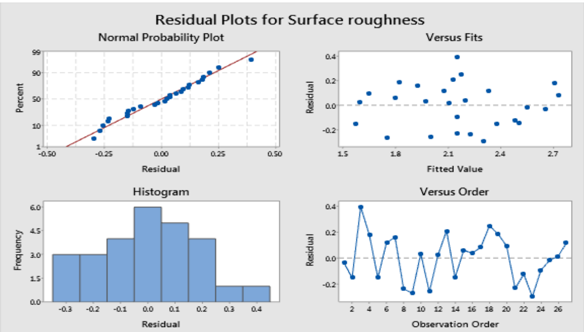

Fig.7 Residual plots of regression model of surface roughness

To check the acceptability of reduced model, ANOVA is performed again, but considering the significant terms and tabulated in table 4, the F value shows considerable improvement of 18.52 compared to 5.1 from table 3. The model displayed at a Confidence level (R2) of 77.01 %. The Residual plots are developed for the surface model of Ra shown in fig. 7. The Probability plot of residual values remains on a line, which indicates the experimental values meet the confidence intervals and the guidelines of sample size. In fitted verses residual plot, the residual values are distributed randomly with constant variance and the points are observed on both sides of zero line. In the order verses residual plot the values fall about the center line randomly. From fig. 7, it is evident that the residuals are not independent and thus correlated. [17,18].

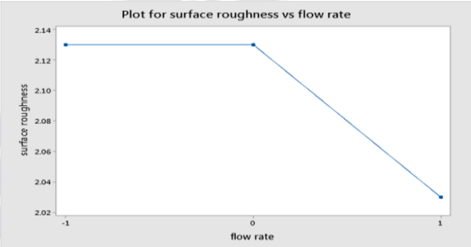

Fig.no.8 (a) Surface Roughness vs Flow rate

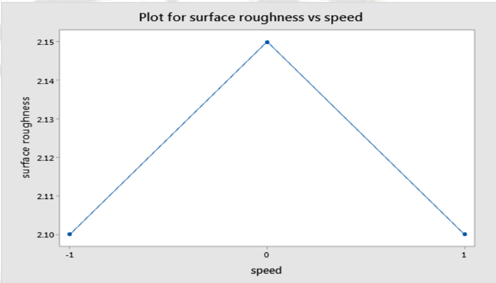

Fig.no.8 (b) Surface Roughness vs speed

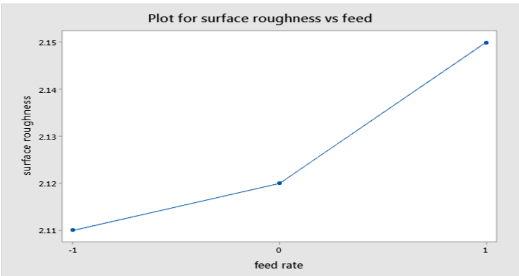

Fig.no.8 (c) Surface Roughness vs feed rate

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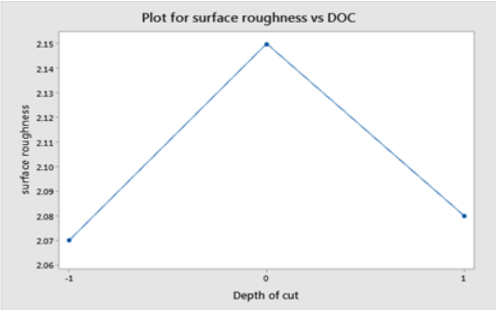

Fig.no.8 (d) Surface Roughness vs DOC

As surface roughness is an output response which needs to be minimized in any machining operation. Fig. no. 8 (a-d) shows the influence of input variables on the surface roughness in turning of EN353 alloy steel using hybrid nanofluid under MQL conditions. From fig no. 8 (a) it is observed that, as the flow rate of MQL increases, there is a slight decrease in the roughness [19-25]. Theoretically the higher cutting speed lowers the roughness; hence from fig no. 8 (b) practically it is correlated as 1500rpm which is the highest speed said to be the optimum condition. The optimum conditions for feed rate and depth of cut is 0.2 mm/rev and 0.5 mm as higher the value higher will be the roughness.

Table 5: Optimum parameters

Optimum Solution	MQL FR	SPEED	FEED	DEPTH OF CUT
	300	1500	0.2	0.5

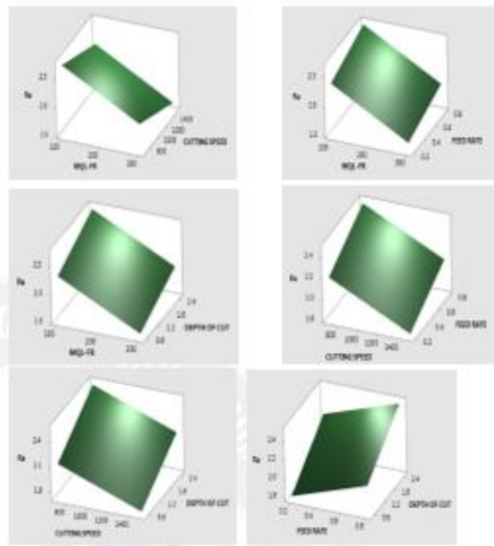

Fig.9 Surface plots of Ra with interaction effect of process

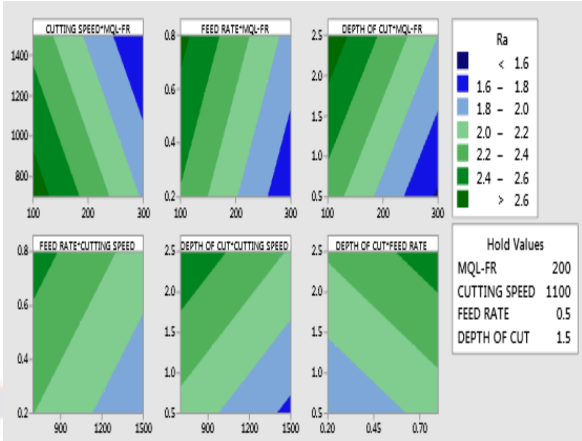

Fig.10 Counter plots of Ra with interaction effect of process parameters

Fig. no. 9 & 10 shows the 3D response surface plots and counter plots with interaction effect of input parameters and their effects with the response values.[26-32] The bright spots indicates the effect of surface roughness (Ra) in connection with input parameters, Hence all the interactions between the variables, especially the effect caused with respect to MQL flow rate to speed, feed and depth of cut are to be more systematic compared with other effects. It is observed from the counter plots to get better surface roughness higher value of MQL flow rate, speed and lower value of feed and depth of cut is to be used.

IV. CONCLUSION

The present paper focuses on effect of hybrid nanofluids in machining of steel alloy at different MQL flow rates using Box-Behnken Design of RSM approach with 4 input variables

- To see the model and variables correlation with respect to its significance over output responses ANOVA was performed successfully. For surface roughness, all the input parameters are said to be significant where MQL flow rate has the major contribution compared to other factors.
- The quadratic model developed for surface roughness i.e. Eq. 3, is validated by calculating the percentage of error between predicted and actual values. The predicted and confirmatory (actual values) experiments have carried out in order to support the accuracy of model developed, shown in table 6. The input parameters assumed here are different from the parameters selected in the design of experiments and it is found that the percentage error is within the range of acceptability i.e. -7.05 to 7.59. Hence, it can be concluded that response surface methodology can develop and predict any output response successfully.

- From the results it can be also concluded that, any change in the maximization of MQL flow leads to minimization surface roughness. The use of Hybrid nanofluid i.e. Al2O3+Cu nanoparticles with water base fluid as lubricant, improved thermal conductivity during machining of alloy steel and showed favorable results compared to its machining standards.

Table 6: Validation experiments for surface roughness

	FR	**Speed**	**Feed**	**DOC**	**Predicted Values (μm)**	**Actual Values (μm)**	**% Error**
Exp 1	60	750	0.3	0.4	2.50	2.68	7.20
Exp 2	120	950	0.6	0.8	2.41	2.24	-7.05
Exp 3	180	1150	0.9	1.2	2.32	2.49	7.33
Exp 4	240	1350	1.2	1.6	2.24	2.41	7.59

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