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Mathematical Modeling and Multi Response Optimization for Improving Machinability of Alloy Steel using RSM, Grey Relational Analysis and Jaya Algorithm

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A B S T R A C T

In order to minimise the difficulties associatedwith selecting conventional coolants in any machining, cutting fluids like vegetable based oils can serve as a viable alternative. Vegetable based oils when used in combination with eco-friendly techniques like MQL/NDM can have a major impact in any machining. In the present paper, performance characteristics of surface roughness and tool wear in machining of EN 36 steel alloy under near dry machining conditions/ minimum quantity lubrication using vegetable based oil lubricant is studied. The input parameters like MQL flow rate, speed, feed and depth of cut for 5 levels are used in the CCD approach of Response surface methodology. For improving the machinability of alloy steel and to predit the values a regression equation is designed and developed between the input parameter and the output parameters. A multi-response optimum model for the output responses was also developed using RSM, GRA and JAYA algorithm, It was observed from the experiment results that JAYA algorithm was proved the best multi-response optimization technique when compared to grey relational analysis and RSM.

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1. INTRODUCTION

Machining plays an important role in converting raw material to a desired shape by metal removal in the form of chips. Lot of heat is generated near tool and workpiece [1, 2] interface due to the development of friction between them, where cutting fluids are employed to overcome this effect [3]. Lubrication plays a vital role in cooling tool and work piece and flushing the chips away from the machining area, machining performance of vegetable based coolants compared to conventional coolants have improved thermal conductivity in maintaining the cutting temperature during machining, between the workpiece and tool interface and also reduces the ecological problems associated with the enviroinment [4]. Sustainable manufacturing is one of the recent trends in current industrial economy, as it is eco-friendly, cost effective, waste free, energy efficient etc [5]. Hence an attempt is made in order to reduce the use of lubricant, with the help of one of the sustainable manufacturing technique [6] i.e. utilizing Minimum Quantity Lubrication (MQL). Lubricants accounts around 16 to 20% of the total manufacturing costs [7], Among different techniques available in the reduction of lubricnt flow in machining, researchers are suggesting MQL [8] as a viable alternate; as it reduces the flow of lubricant by spraying the mixture of coolant with air [9]. In MQL machining the compressed air mixed with the coolant [10], where the flow of the air need to maintain in bars and flow of coolant need to maintain below 300ml/h. Several researches have been carried out through MQL technique [11], where as in the present paper an attempt is made in order to study the charecteristics of MQL for different flow rates. The RSM is a statistical and mathematical tool used to develop, optimize and improve a process [12]. RSM composed of design with an aim of determining the optimum functioning of an industrial efficiency, considering least

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experimental effort [13]. The inputs are known as factors or variables and the outputs known as response that generates by the system [14]. RSM comprises of developing experimental designs, processing of regression model and optimization [15, 16]. In the present paper the RSM methodology is used to develop, optimize and improve the process to minimize the surface roughness and tool wear for the selected variables. A multi response optimization using the GRA, advanced and evolutionary technique Jaya algorithm is developed to check the performance characteristics of the objective function.

2. MATERIAL AND METHODS

The experimentation is carried out through central composite design (CCD) of RSM, In CCD, a design comprises of k factors where distance from axial point to the design center is $\alpha = 2^{k/4}$ [17]. Four independent variables namely MQL flow rate, speed, feed and depth of cut were used for experimentation; hence, based on the input factor k, the value of α is to be considered as 2. The coded input variables with 5 levels are tabulated in Table 1 the output responses selected are tool wear and surface roughness. The experimental design is generated with the help of Minitab 19 software and the sequence of experiments for turning operations is tabulated in Table 2, a total of 31 experiments were performed as per the standard order design sequence and the corresponding results surface roughness and cutting temperature is measured accordingly.

The experiments were performed on high speed CNC machine of LOKESH TL20 Max model CNC Machine shown in Figure 1, The MQL setup was developed using five different “Spray gun” maintaining the flow rates of 50, 100, 150, 200 and 250ml/h with an air compressor maintaining a constant air pressure of 2 bars [9] (layout shown in Figure 3). The cutting tools selected for turning are TNMG Uncoated carbide tool. EN 36 Alloy steel is used as work piece material with carbon content of 0.16%. En 36 is the most widely used Alloy Steel as it has wide applications in manufacturing of gears, shafts, pinions, camshafts and gudgeon pins etc. The dimensions of the work piece, selected for the experiment is 32mm diameter X 150mm length shown in Figure 2. The coolant used is vegetable oil based cutting fluid, which is processed by mixing sunflower oil with triethanol amine and oleic acid, maintained in the ratio of 2:1:2 respectively. The mixture of 40ml of sunflower oil, 40 ml of oleic acid and 20 ml of triethanol amine was taken and stirred thoroughly using a mechanical stirrer, the homogeneous mixture prepared is dissolved in water at a ratio of 1:20.

TABLE 1. Input Variables and Their Levels

Factors	Levels Units	Lower (-2)	Low (-1)	Centre (0)	High (+1)	Higher (+2)
Mql- Flow Rate (A)	ML/HR	50	100	150	200	250
Speed (B)	RPM	700	900	1100	1300	1500
Feed (C)	MM/REV	0.1	0.3	0.5	0.7	0.9
Depth Of Cut (D)	MM	0.5	1.5	2.5	3.5	4.5

TABLE 2. Central Composite design Experimentation with Surface roughness and Tool wear values

MQL flow rate	SPEED	FEED	DOC	Ra	TW
150	1100	0.5	2.5	2.21	0.44
200	1300	0.3	1.5	1.76	0.31
200	900	0.7	3.5	2.22	0.57
100	1300	0.3	3.5	2.54	0.48
200	900	0.7	1.5	2.12	0.59
100	1300	0.3	1.5	2.51	0.37
200	1300	0.3	3.5	1.96	0.41
200	900	0.3	3.5	2.23	0.42
150	1100	0.9	2.5	2.58	0.61
50	1100	0.5	2.5	2.67	0.55
200	900	0.3	1.5	2.19	0.39
150	1100	0.5	2.5	2.24	0.45
150	1100	0.5	2.5	2.23	0.44
150	700	0.5	2.5	2.31	0.41
150	1100	0.5	4.5	2.61	0.44
200	1300	0.7	1.5	2.03	0.51
150	1100	0.5	2.5	2.2	0.45
100	1300	0.7	3.5	2.45	0.56
150	1100	0.5	2.5	2.29	0.49
250	1100	0.5	2.5	1.84	0.45
150	1100	0.5	2.5	2.21	0.43
100	900	0.3	1.5	2.56	0.4
100	900	0.7	1.5	2.51	0.57
100	1300	0.7	1.5	2.47	0.61
150	1100	0.5	2.5	2.25	0.43
150	1100	0.5	0.5	2.34	0.39
100	900	0.7	3.5	2.51	0.59
200	1300	0.7	3.5	2.03	0.63
150	1100	0.1	2.5	2.21	0.21
100	900	0.3	3.5	2.51	0.46
150	1500	0.5	2.5	2.2	0.51

Figure 1. CNC machine

Figure 2. EN36Alloy steel

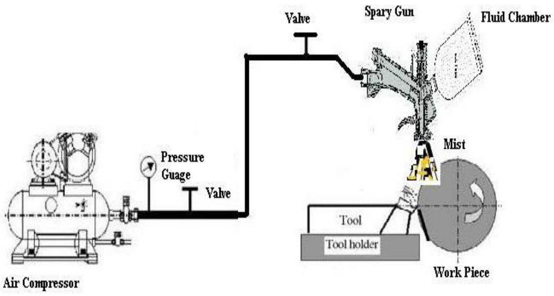

Figure 3. Layout of MQL setup

The Surface roughness (Ra) is measured using MITUTOYO surface roughness tester shown in Figure 4, the results of corresponding Ra values are tabulated in Table 2. Tool flank wear is measured directly using tool makers microscope as shown in Figure 5 at a 100X magnification.

Figure 4. Surface Roughnes tester

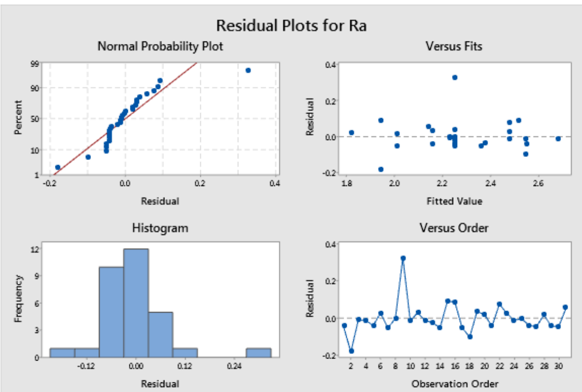

Figure 5. Residual plots for surface roughness regression model

3. RESULTS AND DISCUSSIONS

The machinability affects of Steel alloy using vegetable based cutting fluid considering the input variables is investigated through RSM approach. Table 2 represents the results of measured surface roughness (Ra) and tool wear (Tw) as per the standard order of sequence. In RSM, the experimental design and regression equation helps in retrieving the response for selected independent input variables [14-20] using the following equation:

$$X = b0 + b1Y1 + b2Y2 + b3Y3 + \ldots + bnYn + e \quad (1)$$

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.

3. 1. Effect of Input Factors on Surface Roughness

Based on the experimental design the Ra measured, in Table 2, the quadratic equation developed by calculating coefficient of regression for surface roughness is given in Equation (2). The ANOVA is performed, to define the significance of the input variable towards output response and to check the model adequacy, are tabulated in Table 3, model F- calculated value is 14.37 which indicates model is significant. The values of P < 0.0500 imply model terms to be significant. In the present work MQL Flow rate, Speed, Depth of cut, DOC * DOC, MQL flow rate * Speed are said to be significant. A value generated > 0.1 indicates the model is not significant. The lack of fit is 0.4 which indicates it is not significant, as lack of fit with Non-significant is good –as it is needed that the model is to be fit [17]. Model showed a correlation coefficient (R2) of 92.63 % value suggesting a satisfactory representation of model. Furthermore the insignificant model terms are eliminated using backward elimination approach in order to fit the full model, hence the regression equation considering second order terms is given by Equation (3).

$$\begin{aligned}Ra=&3.201-0.00048\ \text{MQL flow rate}+0.000394\ \text{SPEED}-1.490\ \text{FEED}-0.310\ \text{DOC}-0.000002\ \text{MQL flow rate*MQL flow rate}\\&-0.000000\ \text{SPEED*SPEED}+0.774\ \text{FEED*FEED}+0.0510\ \text{DOC*DOC}-0.000005\ \text{MQL flow rate*SPEED}\\&+0.00275\ \text{MQL flow rate*FEED}+0.000475\ \text{MQL flow rate*DOC}+0.000531\ \text{SPEED*FEED}\\&+0.000037\ \text{SPEED*DOC}-0.044\ \text{FEED*DOC}\end{aligned} \quad (2)$$

TABLE 3. ANOVA table of RSM for Surface Roughness

Source	DoF	Adj SS	Adj MS	F-Value	P-Value
Model	14	1.425	0.102	14.37	0
Linear	4	1.248	0.312	44.04	0
MQL flow rate	1	1.118	1.118	157.8	0
SPEED	1	0.073	0.073	10.25	0.006

FEED	1	0.028	0.028	3.95	0.064
DOC	1	0.029	0.029	4.15	0.039
Square	4	0.101	0.025	3.55	0.029
MQL flow rate* MQL flow rate	1	0.000	0.000	0.07	0.8
SPEED*SPEED	1	0.000	0.000	0.07	0.8
FEED*FEED	1	0.027	0.027	3.87	0.067
DOC*DOC	1	0.074	0.074	10.48	0.005
2-Way Interaction	6	0.077	0.013	1.8	0.162
MQL flow rate*SPEED	1	0.046	0.046	6.53	0.021
MQL flow rate*FEED	1	0.012	0.012	1.71	0.21
MQL flow rate*DOC	1	0.009	0.009	1.27	0.276
SPEED*FEED	1	0.007	0.007	1.02	0.328
SPEED*DOC	1	0.001	0.001	0.13	0.726
FEED*DOC	1	0.001	0.001	0.17	0.683
Error	16	0.113	0.007		
Lack-of-Fit	10	0.108	0.011	11.24	0.4
Pure Error	6	0.006	0.001		
Total	30	1.539			

To check the acceptability of reduced model, ANOVA is performed again, but considering the significant terms and tabulated in Table 4. It is observed that the F value shows considerable improvement of 33.08 compared to 14.37 from Table 3. The model displayed at a Confidence level (R^2) of 86.87 %. To validate the regression Equation (3) the input parameters other than the selected values are considered to predict the equation as shown in Table 5. A conformation test is also carried out based on the selected values and the percentage of error is calculated by using the below Equation (4), hence the percentage of error found to be within the range of acceptance i.e. -5.31 to 5.29.

$$Ra=2.534 + 0.00160\ \text{MQL flow rate} + 0.000531\ \text{SPEED} - 0.2097\ \text{DOC} + 0.0489\ \text{DOC*DOC} - 0.000005\ \text{MQL flow rate*SPEED} \tag{3}$$

$$\text{Percentage of error} = \frac{\text{Actual value} - \text{Predicted value}}{\text{Predicted value}} \times 100 \tag{4}$$

To check the adequacy of model, Residual plots are developed for the surface model of Ra shown in Figure 5. 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 Figure 7, it is evident that the residuals are not independent and thus correlated [17].

TABLE 4. ANOVA table of RSM for modified Surface Roughness

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	5	1.333	0.2675	33.08	0
Linear	3	1.222	0.4066	50.31	0
MQL flow rate	1	1.110	1.1180	138.32	0
SPEED	1	0.076	0.0726	8.98	0.006
DOC	1	0.0294	0.0294	3.64	0.048
Square	1	0.0708	0.0708	8.72	0.007
DOC*DOC	1	0.0708	0.0704	8.72	0.007
2-Way Interaction	1	0.0463	0.0463	5.72	0.025
MQL flow rate*SPEED	1	0.0463	0.0462	5.72	0.025
Error	25	0.2027	0.0080		
Lack-of-Fit	19	0.1963	0.0103	10.8	0.4
Pure Error	6	0.0054	0.0006		
Total	30	1.5388			

TABLE 5. Surface Roughness- Validation experiments

	A	B	C	D	Predicted Values	Actual Values	% Error
Exp 1	60	750	0.3	0.4	2.73	2.68	-1.73
Exp 2	120	950	0.6	0.8	2.52	2.39	-5.31
Exp 3	180	1150	0.9	1.2	2.22	2.17	-2.09
Exp 4	240	1350	1.2	1.6	1.8	1.9	5.29

As surface roughness is an output response, which is required to be minimized in any machining operation. Figures 6 and 7 show the 3D response surface and counter plots with interaction effects of process parameters and their effects on the response value; from the surface plots 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 when compared. From counter plots to obtain minimum surface roughness the suggested MQL flow rate lies above 200 ml/h, speed above 1200rpm, feed below 0.4mm/rev and depth of cut between 1 to 3.5mm.

3. 2. Effect of Input Factors on Tool Wear

Based on the experimental design the tool wear is measured and the quadratic equation developed by calculating

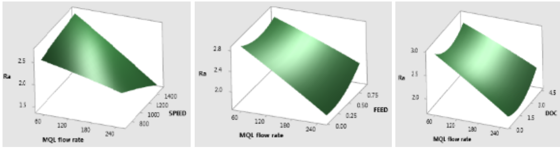

Figure 6. (a) 3-D Surface plot of surface roughness on, MQL-flow rate vs speed (left),MQL-flow rate vs feed (center) and MQL-flow rate vs depth of cut (right)

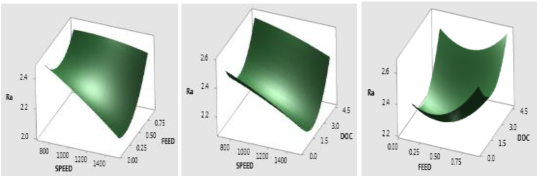

Figure 6. (b) 3-D Surface plot of surface roughness on, speed vs feed (left), speed vs depth of cut (center) and feed vs depth of cut (right)

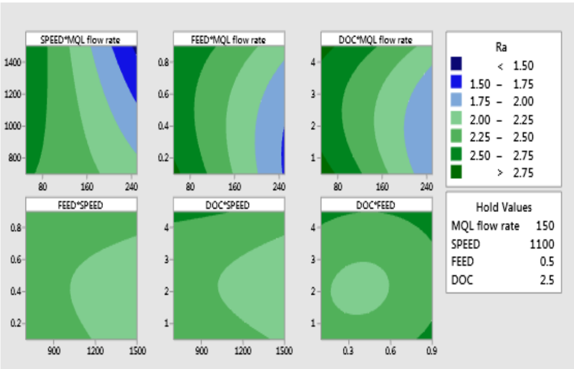

Figure 7. Counter plots for surface roughness with interaction of process parameters

coefficient of second order regression at confidence level (R2) of 84.52% with significant terms is given by Equation (5) [17]. The plots of residual the developed model of tool wear is plotted and shown in Figure 9. As it is observed, the results are shown shown in good arrangement.

TW=0.4091 - 0.002748 MQL flow rate + 0.4563 FEED + 0.01958 DOC+ 0.000008 MQL flow rate*MQL flow rate (5)

A conformation test is performed to validate the tool wear regression Equation (5) as shown in Table no. 6. The percentage of error found to be within the range of acceptance i.e. -13 to +14. Figures 9 and 10 show the 3D response surface plots and counter plots with the interaction effect of process parameter for tool wear, 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. From counter effects it can be observed that to get minimum tool wear the MQL flow rate above 100 ml/h, speed in between 900 to 1500 rpm, feed less than 0.3 mm/rev and depth of cut less than 2mm is suggestable.

3. 3. Formulation of Multi Objective Function

The optimization of two responses namely tool wear and surface roughness in machining of alloy steel under MQL conditions considering the process parameters is studied

TABLE 6. Validation experiments for tool wear

	A	B	C	D	Predicted Values	Actual Values	% Error
Exp 1	60	750	0.3	0.4	0.42	0.48	14.9
Exp 2	120	950	0.6	0.8	0.48	0.42	-13.22
Exp 3	180	1150	0.9	1.2	0.61	0.57	-6.22
Exp 4	240	1350	1.2	1.6	0.79	0.82	3.89

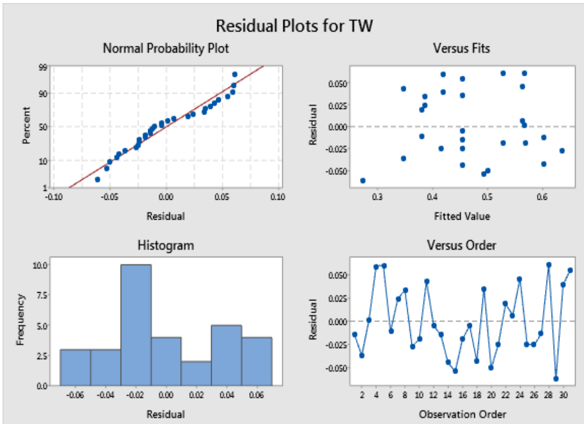

Figure 8. Residual plots for Tool Wear regression model

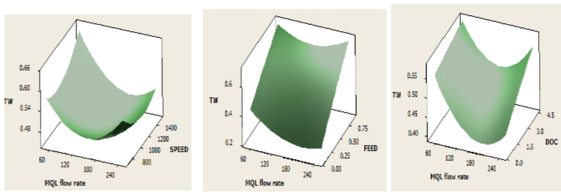

Figure 9. (a) 3-D Surface plot of Tool wear on MQL-flow rate vs speed (left), MQL-flow rate vs feed (center) and MQL-flow rate vs depth of cut (right)

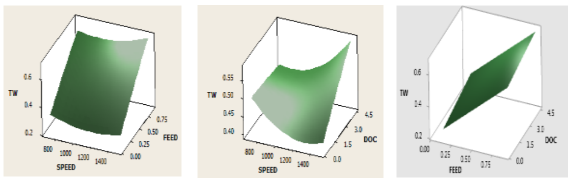

Figure 9. (b) 3-D Surface plot of surface roughness on speed vs feed (left), speed vs depth of cut (center) and feed vs depth of cut (right)

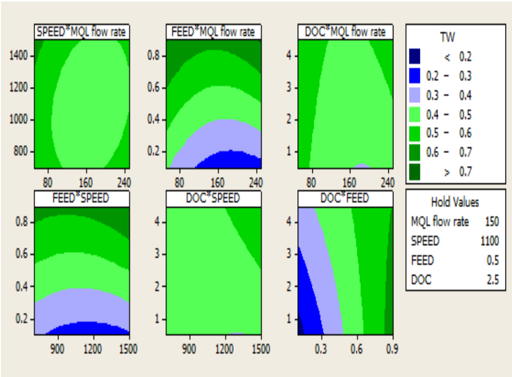

Figure 10. Counter plots of tool wear with interaction of process parameters

and simultaneously a multi objective is formulated for minimization of the output responses. To study the multi objective function a combined objective function is generated to convert multi objective to a single-objective mathematical optimization function, which is given by Equation (6).

$$\text{Min COF} = W1 * (Ra/ Ra\ min) + W2 * (Tw/ Tw\ min) \quad (6)$$

where, W1 and W2 indicates the weights granted to the responses and assigned equal weights of 0.5. After individual optimization the minimum surface roughness adopted to be 1.76µm and tool wear 0.21 mm from Table 2. The normalized multi-objective function to a single objective function is obtained from Equations (3) and (5) is given as Equation (7). The input variables selected are minimum and maximum values of MQL flow rate, speed, feed and depth of cut.

$50 \leq$ MQL flow rate ≤ 250
$700 \leq$ Speeed ≤ 1500
$0.1 \leq$ feed ≤ 0.9
$0.5 \leq$ depth of cut ≤ 4.5

$$\text{COF}=1.693-0.005\ \text{MQL flow rate} + 0.00014\ \text{SPEED} + 1.085\ \text{FEED} - 0.0132\ \text{DEPTH OF CUT} + 0.0000190\ \text{MQL flow rate* MQL flow rate} - 0.00000142\ \text{MQL flow rate* SPEED} + 0.013\ \text{DEPTH OF CUT* DEPTH OF CUT} \quad (7)$$

JAYA Algorithm

JAYA [18] (Victory in Sanskrit), is an evolutionary optimization technique formulated for solving constrained and unconstrained optimization problem developed by Rao [19]. The Algorithm is based on the concept of shifting towards best solution by avoiding worst solution. For optimization unlike other algorithms, Jaya algorithm requires only basic idea on terms like design variables, objective function, population size and no. of iterations. Figure 11 shows the flow chart of JAYA algorithm, in the present work the objective function is considered to be Equation (7) for minimization of surface roughness and tool wear. The iteration i, with m number of input factors j=1, 2, 3, 4 (MQL flow rate, speed, feed and depth of cut) for population k=1, 2, 3… is considered to modify the best and worst solutions using the Equation (8) [20].

$$A'_{j,k,i} = A_{j,k,i} + r1_{j,i}\ ((A_{j,b,i}) - |A_{j,k,i}|) - r2_{j,i}\ ((A_{j,w,i}) - |A_{j,k,i}|) \quad (8)$$

where Aj,b,i and Aj,w,i is the input variable j for the corresponding best and worst function at i^{th} iteration. A' j,k,i is the modified solution of A j, k, i and r1,j,i and r2,j,i are two random numbers [21]. The Random numbers within the range of input variables are considered and corresponding combined objective function (COF – Equation (8)) is calculated and tabulated in Table 7 for a population size of 6. In the present work the objective is to minimize COF, hence the first row (smallest value) is marked as best solution and fifth row (highest value) is marked as worst. Latter the solution is modified using Equation (8) considering all the variables for each row and column and tabulated in Table 8. On comparing initialize and modified solution row wise the best solution is opted for the 1^{st} iterations, here the modified solution is better than iteration solution hence modified values are considered to be best solutions. As the iterations are continued till final objective has no changes and the last value is considered to be optimum solutions. Using matlab, considering the JAYA algorithm code, a program is run to simulate at various plans (i.e. A to F).

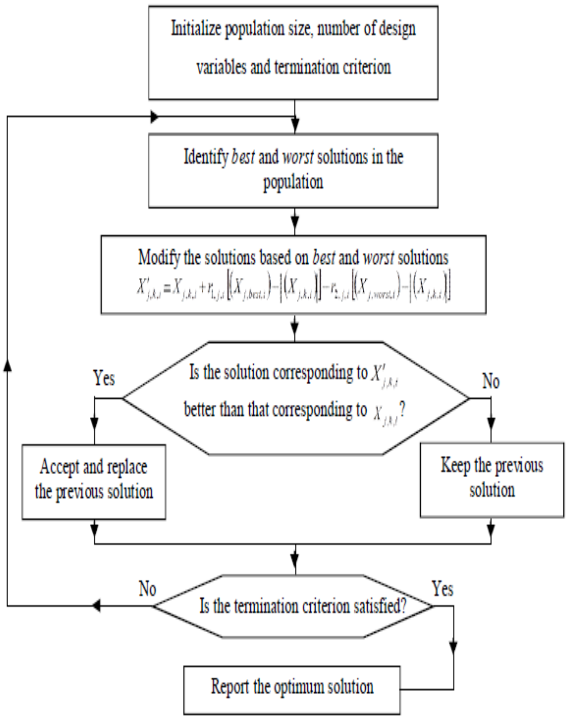

Figure 11. Flow chart of JAYA algorithm

TABLE 7. Initialization of solution

MQL Flow Rate (A)	Speed (B)	Feed (C)	Depth of Cut (D)	COF	
120	1000	0.25	1.2	1.551	Best
170	870	0.38	1.3	1.721	
130	1300	0.48	1.9	1.849	
160	1400	0.52	2.6	1.875	
230	1125	0.62	3.4	2.116	worst
225	1325	0.33	4	1.805	

TABLE 8. Modified and Best solution

A	B	C	D	COF
87	962.5	0.14	0.54	1.4977
132	845.5	0.24	0.47	1.5767
96	1232.5	0.33	1.01	1.7463
123	1322.5	0.36	1.64	1.7257
245	1280	0.4	2.9	1.8474
181.5	1255	0.19	2.9	1.5419

TABLE 9. Performance of machining parameters using JAYA algorithm

Plan	A	B	C	D	COF	Ra	Tw
A	245	1280	0.4	2.9	1.847	1.84	0.46
B	245	1100	0.22	2	1.644	1.94	0.36
C	245	1280	0.22	2	1.607	1.81	0.36
D	245	1460	0.22	1.1	1.545	1.74	0.34
E	245	1460	0.1	2.9	1.485	1.72	0.32
F	245	1460	0.1	1.1	1.415	1.74	0.28

For Plan A, Population size=6, No. of iterations= 1
For Plan B, Population size=10, No. of iterations= 5
For Plan C, Population size=15, No. of iterations= 10
For Plan D, Population size=20, No. of iterations= 20
For Plan E, Population size=15, No. of iterations= 25
For Plan F, Population size=15, No. of iterations= 25

From Table 9, the individual responses of surface roughness and tool wear is also calculated from regression Equations (3) and (5) for various plans and it is observed that the COF, Ra and Tw for the last plan F is very minimum (as our objective is to minimize) and it is considered to be optimum solution.

3. 4. Optimization by Grey Relational Analysis (GRA)

From Figure 12 the procedure for generating optimum parameters for multi response optimization using grey relational analysis [22] is shown, the corresponding grey relational coefficient of Ra and Tw values are shown in the Table 10 to minimize the response [23].

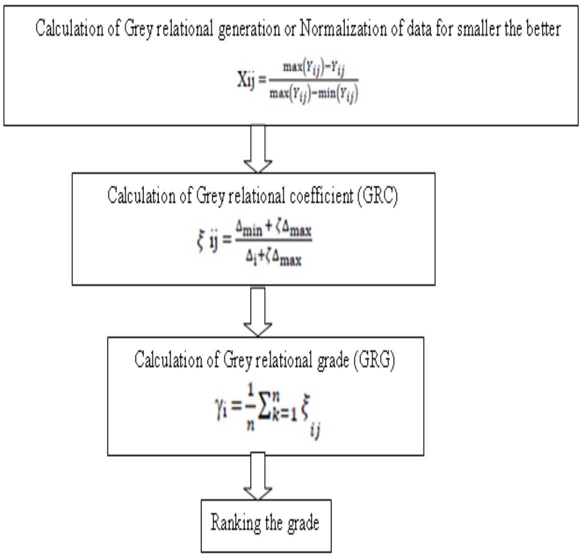

Figure 12. Flow chart of Grey Relational Analysis

TABLE 10. Grey Relational Analysis for Ra and T_w

Exp.No	Normalized values		Grey relational coefficient		GRG	GRG S/N ratio	Rank
	Ra	Tw	Ra	Tw			
1	0.45	0.51	0.48	0.5	0.49	6.2	9
2	0.76	1	0.68	1	0.84	1.53	1
3	0.14	0.49	0.37	0.5	0.43	7.27	22
4	0.36	0.14	0.44	0.37	0.4	7.89	25
5	0.1	0.6	0.36	0.56	0.46	6.8	19
6	0.62	0.18	0.57	0.38	0.47	6.51	17
7	0.52	0.78	0.51	0.69	0.6	4.39	4
8	0.5	0.48	0.5	0.49	0.5	6.09	7
9	0.05	0.1	0.34	0.36	0.35	9.1	31
10	0.19	0	0.38	0.33	0.36	8.93	30
11	0.57	0.53	0.54	0.51	0.53	5.58	5
12	0.43	0.47	0.47	0.49	0.48	6.44	16
13	0.45	0.48	0.48	0.49	0.48	6.29	13
14	0.52	0.4	0.51	0.45	0.48	6.33	14
15	0.45	0.07	0.48	0.35	0.41	7.68	24
16	0.29	0.7	0.41	0.63	0.52	5.69	6
17	0.43	0.52	0.47	0.51	0.49	6.24	11
18	0.17	0.24	0.38	0.4	0.39	8.26	26
19	0.33	0.42	0.43	0.46	0.45	7.03	20
20	0.43	0.91	0.47	0.85	0.66	3.63	3
21	0.48	0.51	0.49	0.5	0.5	6.1	8
22	0.55	0.12	0.53	0.36	0.44	7.06	21
23	0.14	0.18	0.37	0.38	0.37	8.57	27

24	0.05	0.22	0.34	0.39	0.37	8.7	28
25	0.48	0.46	0.49	0.48	0.48	6.29	12
26	0.57	0.36	0.54	0.44	0.49	6.21	10
27	0.1	0.18	0.36	0.38	0.37	8.71	29
28	0	0.7	0.33	0.63	0.48	6.37	15
29	1	0.51	1	0.5	0.75	2.48	2
30	0.4	0.18	0.46	0.38	0.42	7.6	23
31	0.29	0.52	0.41	0.51	0.46	6.74	18

The highest value of GRG obtained through grey relational coefficient, considered as the stronger relational degree and the ranking is obtained accordingly, it is observed that experiment no.2 obtained 1st rank with highest GRG. The optimum level of input factors is determined using results of GRG S/N ratio. Table 11 shows the optimum levels for machining at MQL flow rate 250ml/h, Speed 1300 rpm, Feed 0.1 mm/rev and depth of cut 0.5 mm, where feed ranked with the highest delta value followed by MQL Flow rate, Depth of cut and Speed. The predicted response is calculated as per the Equation (9) which is in good arrangement when compared with the confirmation test results tabulated in Table 12.

$$\text{Predicted Response} = A5 + B4 + C1 + D1 - 3 * (Yij) \qquad (9)$$

A5, B4, C1 and D1 are the corresponding input parameters of GRG, Yij- Average of GRG.

3. 5. Optimization by RSM

The multi response optimization using perturbation curve (shown in Figure 14) of response surface methodology (RSM) is carried out through minitab 19 statistical software and the optimum values are tabulated in Table 13.

3. 6. Comparisons of Confirmation Test Results

The multi response optimization is performed in order to improve the performance characteristics using grey relational analysis, response surface methodology and JAYA algorithm. A confirmation test is performed to

TABLE 11. Response Table for GRG S/N

Level	MQL flow rate	Speed	Feed	DOC
1	8.933	6.331	2.483	6.213
2	7.912	7.209	5.83	6.302
3	6.417	6.343	6.556	6.226
4	5.463	6.167	7.546	7.073
5	3.628	6.743	9.105	7.682
Delta	5.305	1.042	6.622	1.469
Rank	2	4	1	3

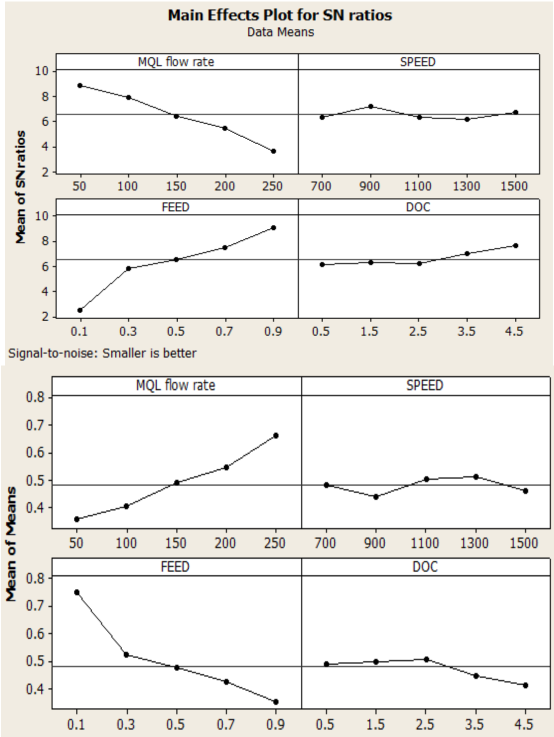

Figure 13. S/N Ratios and Mean plots of GRG

TABLE 12. Confirmation test results of GRA

	Best parameters value out of 31 experiments with GRG are considered to be initial parameters	Optimum parameters	
		Predicted values	Experiment values
Level	A4, B4, C2, D2	A5, B4, C1, D1	A5, B4, C1, D1
Surface Roughness	1.76		1.72
Tool Wear	0.31		0.27
GRG	0.84	0.96	0.92

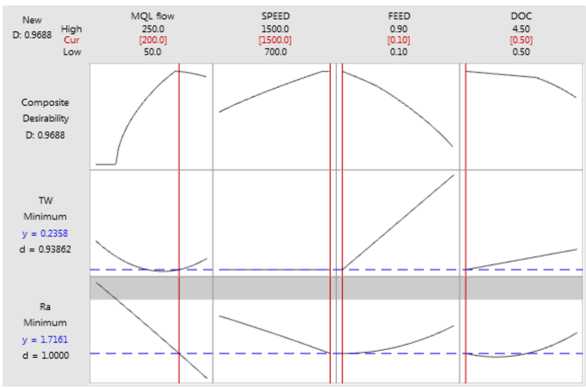

Figure 14. Multi response optimized values with Perturbation curve

TABLE 13. Multi Response optimized values using RSM

Optimum Solution	MQL flow rate	Speed	Feed	DOC
	200	1500	0.1	0.5

validate the model. From Table 14, confirmation test is performed for all the optimum parameters generated through various techniques. The objective is to minimize the dependent variables; it is observed that there was a considerable reduction of surface roughness and tool

TABLE 14. Comparisons of Confirmation test results of JAYA, GRA &RSM

	Initial Parameters	JAYA	GRA	RSM	Change in the results in percentage for the optimum cutting Conditions towards initial parameter settings		
					JAYA	GRA	RSM
MQL Flow rate	200	245	250	200			
Speed	1300	1460	1300	1500			
Feed	0.3	0.1	0.1	0.1			
Depth of cut	1.5	1.1	0.5	0.5			
Ra	1.76	1.67	1.72	1.7	5.11% reduction	2.27% reduction	3.40% reduction
Tw	0.31	0.24	0.26	0.29	22.58% reduction	16.12% reduction	6.45% reduction

wear when compared with initial parameters for all the techniques. The initial parameters selected are the best parameters values out of 31 experiments. The JAYA algorithm shows a reduction percentage of 5.11 % surface roughness and 22.58% toolwear when compared to grey analysis 2.27% Ra and 16.12% Tw, RSM 3.40% Ra and 6.45% Tw.

4. CONCLUSION

The present paper focuses on minimization of surface roughness and tool wear in order to improve the machining of alloy steel under MQL conditions using RSM, GRA and JAYA algorithm techniques. RSM Methodology is implemented and validated successfully in order to study the effect of variables; a quadratic model is developed for surface roughness and tool wear individually and experiments have carried out to confirm the accuracy of the developed model, From the results, it can be concluded that response surface methodology model can predict and develop any output response successfully. From 3D surface and counter plots, there was a considerable impact on the selected independent variables with respect to dependent variables where MQL Flow rate and depth of cut has major impact compared to other variables. Further, the performance characteristics of Surface roughness and Tool wear are identified by multi response optimization using Perturbation curve of RSM Methodology, Grey relational analysis and JAYA algorithm. A confirmation test was performed. At the obtained optimum conditions and compared, the optimum parameters of JAYA algorithm showed better reduction in minimization of surface roughness and tool wear (Figure 15). It is also concluded that machining using MQL at a flow rate of more than

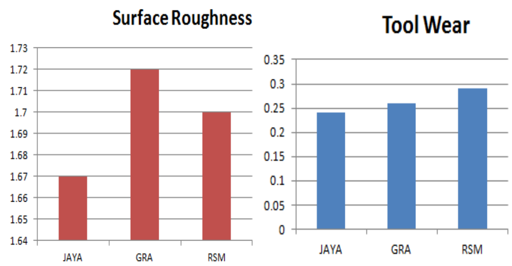

Figure 15. Comparison of confirmation results of Ra and Tw among all the techniques

200ml/h gives better result for individual and multi response optimization using any technique.

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Persian Abstract

چکیده

به منظور به حداقل رساندن مشکلات مربوط به انتخاب خنک کننده های معمولی در هر ماشینکاری ، برپایه روغنهای گیاهی می تواند به عنوان یک جایگزین مناسب عمل کند. روغنهای گیاهی در ترکیب با تکنیکهای سازگار با محیط زیست مانند MQL/NDM می توانند تأثیر عمده ای در هر نوع ماشینکاری داشته باشند. در مقاله حاضر ، ویژگی های عملکرد زبری سطح و سایش ابزار در ماشینکاری آلیاژ فولاد EN 36 در شرایط ماشینکاری تقریبا خشک/ حداقل مقدار روغن کاری با استفاده از روان کننده روغن گیاهی مورد مطالعه قرار گرفته است. پارامترهای ورودی مانند سرعت جریان MQL ، سرعت ، تغذیه و عمق برش برای ۵ سطح در رویکرد CCD روش سطح پاسخ استفاده می شود. برای بهبود قابلیت ماشینکاری فولاد آلیاژی و پیش تعیین مقادیر ، یک معادله رگرسیون بین پارامتر ورودی و پارامترهای خروجی طراحی و توسعه یافته است. یک مدل

بهینه چند پاسخ برای پاسخهای خروجی نیز با استفاده از الگوریتم RSM، GRA و JAYA توسعه داده شد ، از نتایج آزمایش مشاهده شد که الگوریتم JAYA بهترین تکنیک بهینه سازی چند پاسخ در مقایسه با تجزیه و تحلیل رابطه خاکستری و RSM است.