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Multi-Response Optimization during Turning of Hardened AISI D3 Tool Steel using Taguchi Coupled with Deng's Method

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ABSTRACT

Manufacturing industries aims at the reduction in usage of cutting fluids to combat Environmental and Ecological issues towards which new techniques are being explored. Hard turning with minimum quantity lubrication is one such technique which can abate the pollution problems associated with the cutting fluids. The present paper deals with the experimental investigation in turning of hardened AISI D3 steel with CVD coated indexable inserts under minimum quantity lubrication using vegetable oils as cutting fluids. An orthogonal array, analysis of variance(ANOVA) and Deng's index are applied to study the performance of input parameters such as insert style, cutting fluid, cutting speed, feed and depth of cut by considering quality characteristics such as surface roughness, material removal rate, interface temperature, specific energy and flank wear. Finally a clear presentation is made for Deng's method.

1.0 Introduction

Modern manufacturing industries thrust on high quality products in terms of surface finish, high production rate, minimum tool wear, economic machining with reduced environmental impact. The selection of cutting fluid not only improves cutting performance but also fulfils a number of requirements which are non-harmful to health for operators, not a fire hazard, no smoke (or) for and cost is less. Cutting fluids are applied to the cutting zone to improve cutting performance. Generally, cutting fluids are used to provide necessary lubrication and to reduce the temperature being encountered between chip-tool interface. In the present work, hardened AISI D3 steel was selected as work material which finds applications in the manufacture of Blanking & Forming dies, press tools, punches, bushes, forming rolls and many more. For the purpose of experimentation, factorial design experiments are considered as per Taguchi DOE. By advocating Taguchi design, a clear understanding of the nature of variation and economical consequences of quality engineering in the world of manufacturing can be clearly got through. In the present study, Deng's similarity approach was performed to combine the multiple performance characteristics in to one numerical score called Deng's index which is an indicative of the optimal process parameter setting. Analysis of variance (ANOVA) is also performed to investigate the most influencing parameters on the surface roughness, metal removal rate, interface temperature, specific energy and flank wear.

2.0 Literature Review

Nalbant et.al.[1] presented an application of the parameter design of the Taguchi method in the optimization of machining parameters for surface roughness in turning of AISI 1030 steel using TiN coated tools. They stated that the parameter design of Taguchi method provides a simple, systematic and efficient methodology for the optimization of the cutting parameters.

S.Tripathy & D.K.Tripathy[2] presented the experimentation on powder mixed electro discharge machining and application of Taguchi method in combination TOPSIS and Grey relational analysis to evaluate the effectiveness of optimizing multiple performance characteristics for PMEDM of H-11 die steel using copper electrode. The effect of process parameters on the response characteristics have been investigated. Analysis of variance and F-test were performed to determine the significant parameters at 95% confidence level. Predicted results have been verified by confirmatory test

Vikas sonkar et al[3] performed the experimentation in drilling of GFRP composites which focuses on the analysis of drill force, torque, surface roughness and delamination behavior as a function of drilling process parameters. It determined an optimal machining environment based on the concept of the Degree of similarity measures between each alternative and an ideal solution using alternative gradient and magnitude.

Papiya Bhowmik etal [4] focused on an experimental investigation into the role of green machining on surface

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Roughness (Ra), in the machining of aluminium AA1050. A comparative study of turning experiments, between VBCFs and MBCFs under various cutting conditions, using neat or straight Sunflower oil and Coconut oil, was conducted using the same machining parameter set-up. Vegetable oils used on the principle of Minimum Quantity Lubrication (MQL) that is oil dropped between the cutting tool and workpiece interface directly. The results show that vegetable oil performance is comparable to that of mineral oil machining. The results show that Vegetable oils have potential to replace the mineral oils.

Ujjwal Kumar etal[5] focuses on an experimental investigation into the role of green machining on surface Roughness (Ra), in the machining of aluminium AA1050. A comparative study of turning experiments, between VBCFs and MBCFs under various cutting conditions, using neat or straight Coconut oil and Castor oil, was conducted using the same machining parameter set-up. Vegetable oils used on the principle of Minimum Quantity Lubrication (MQL) that is oil dropped between the cutting tool and workpiece interface directly. The that vegetable oil performance is comparable to that of mineral oil machining. The results show that Vegetable oils have potential to replace the Mineral oils.

Hossein safari and Ehsan Khanmohammadali [6] proposed a new MADM method. This similarity based method effectively makes use of ideal solution concept in such a way that the most preferred alternative should have highest degree of similarity to the positive ideal solution and the lowest degree of similarity to the negative ideal solution. The overall performance index of each alternative with in all criteria is determined based on the concept of degree of similarity between each alternative and the ideal solution using alternative gradient and magnitude

M.Y Wang & T.S. Lan[7] presents Orthogonal array of Taguchi experiment where in four parameters like cutting speed, feed rate, tool nose run off with three levels in optimizing the multi-objective such as surface roughness, tool wear and material removal rate in precision turning on CNC lathe. For the purpose of multi response optimization, Grey relational analysis was employed.

Dinesh kumar kasdekar and Vishal parashar [8] carried out experimentation on EDM using En-353 steel which highlights the application of technique for order preference by similarity to an ideal solution. In this TOPSIS, SAW based MCDM methods are used and conducted study through computational experiments.

Thaman Balgassim etal[9] conducted experimentation on EDM machine using AISI D3 tool steel. An L9 orthogonal array based on Taguchi method is used to conduct a series of experiments to optimize the EDM parameters. Experimental data were evaluated statistically by analysis of Variance (ANOVA). The experimental results have given optimal combination of input parameters which give the optimum surface finish of machined surface

J S Dureja etal[10] investigated tool wear (flank wear) and surface roughness during finish hard turning of AISI D3 steel (58HRC) with coated carbide (TiSiN-TiAlN coated) cutting tool. Taguchi L9 $(3)^3$ orthogonal array has been applied for experimental design. S/N ratio and ANOVA analyses were performed to identify significant parameters influencing tool wear and surface roughness. The cutting speed and feed were the most significant factors influencing tool wear (flank wear), and feed is the most significant factor influencing surface roughness (Ra). Mathematical models for both response parameters i.e. tool wear and surface roughness was obtained through regression analysis. The confirmation experiments carried out at optimal combination of parameters given by Taguchi's analysis, predicted the response factors with less than 5% error. In addition, Desirability function module in RSM was applied to arrive at the optimal setting of input parameters to minimize tool wear and surface roughness. The optimal solution provided by desirability function optimization was compared with the optimal setting of parameters given by Taguchi analysis. The optimization results provided by both techniques are in close proximity.

Varaprasad BH etal[11] developed a model and predict tool flank wear of hard turned AISI D3 hardened steel using Response Surface Methodology (RSM). The combined effects of cutting speed, feed rate and depth of cut are investigated using contour plots and surface plots. RSM based Central Composite Design (CCD) is applied as an experimental design. Al_2O_3/TiC mixed ceramic tool with corner radius 0.8 mm is employed to accomplish 20 tests with six centre points. The adequacy of the developed models is checked using Analysis of Variance (ANOVA). Main and interaction plots are drawn to study the effect of process parameters on output responses.

3.0 Experimentation

The work material selected for this experiment is hardened AISI D3 tool steel of 40 mm diameter, length 100 mm. The chemical composition of AISI D3 steel has been done by chemical Analyzer and is reported as below in table1 In the present study, five turning parameters were selected with three levels as shown in Table.2. The experimentation was carried out using L27 orthogonal array based on Taguchi design of experiments. The experimental conditions are presented in Table. 3

Table1. Chemical Analysis report.

Element	C	Si	Mn	P	S	Cr	V	W
Specified values	2.00 - 2.35	0.10 - 0.60	0.10 - 0.60	0.03 max	0.03 max	11.00 - 13.50	1.00 max	1.00 max
Observed values	2.07	0.406	0.457	0.02	0.029	11.28	0.037	<0.003

Table2. Process parameters and their levels.

Turning parameters	Notation	Level 1	Level 2	Level 3
Insert style	IS	DNMG	TNMG	CNMG
Cutting fluid	CF	Castor oil	Palm oil	Ground nut oil
Cutting speed, (m/min)	V	100	150	200
Feed, (mm/rev)	F	0.05	0.07	0.09
Depth of cut, (mm)	d	0.10	0.15	0.20

The turning tests were carried out on Kirloskar model centre lathe machine (Figure 2-3) to determine the responses characteristics for various runs of experiment.

Surface roughness is measured using "SJ 201-P" surface roughness measuring instrument.

The metal removal rate (mm^3/sec) is calculated using formula:

$$MRR = [\pi/4(D_1^2-D_2^2)\ L]/t\ mm^3/sec \qquad \text{Eq. 1}$$

Where, D_1 = Diameter of the work piece before turning.mm
D_2 = Diameter of the work piece after turning.mm
L = Length of turning, mm
t = Machining time, sec

Specific energy is obtained by considering the ratio between Power consumed and material removal rate. Flank wear is measured by using Tool maker's microscope.

Table3. Experimental condition.

Machine used	Turn master 35 conventional lathe,
power:	4 HP
Work material	AISI D3 steel with 45 HRC
Size of work piece	Diameter 40 mm x 100 mm
Cutting length	70 mm
Cutting tool holder	PDJNR 2020M15 WIDAX, MTJNR 2020K16 WIDAX PCLNR 2020K12 V tool
Cutting insert	DNMG 150608 EN-TMR , TNMG160408 EN- TM CNMG 120408 EN- TMR
MQL supply	Castor oil, Palm oil and ground nut oil (500 ml/ hour)
Cutting parameters	
Insert style	DNMG, TNMG and CNMG
Cutting fluid	Castor oil(CO), Palm oil(PO) and Ground nut oil (GO)
Cutting velocity	100-200 m/min
Feed	0.05-0.09 mm/rev
Depth of cut	0.10-0.20 mm
Response variables	Surface roughness, SR(µm), Metal removal rate MRR(mm^3/sec), Interface temperature, IT(^{0}C) Specific energy, SE(J/mm^3) and Flank wear, FW(mm)

The different styles of CVD coated inserts and the corresponding tool holders are shown in figure 1

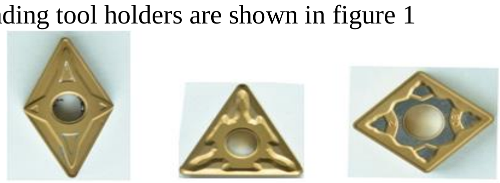

Fig 1. CVD coated DNMG, TNMG and CNMG cutting inserts.

The turning tests were carried out on Kirloskar model centre lathe machine presented in Figures 2-3 to determine the responses characteristics for various runs of experiment.

Fig.2. Kirloskar model Turn master 35 centre lathe.

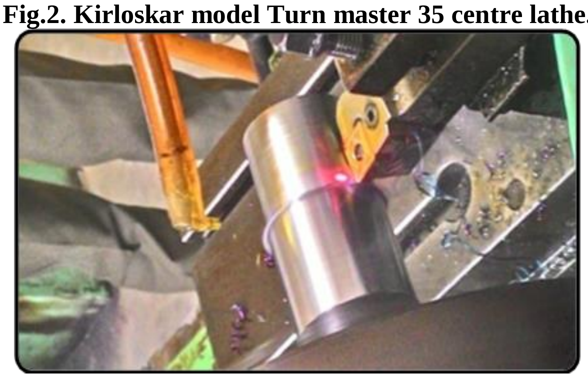

Fig.3. Cutting fluid dropping on cutting zone.

4.0 Methodology

4.1 Entropy approach for weight determination

Entropy method is one of the well-known and widely used methods to calculate the criteria of decision weights [12].

Decision weights increases the importance of criteria and is usually categorized into two types. One is subjective weight which is determined by the knowledge and experience of experts or individuals, and the other is objective weight which is determined mathematically by analyzing the collected data. Here, it is an objective weighting method. W_1, W_2, W_3, W_4 and W_5 are weights assigned to the SR, MRR, IT, SE and FW which are respectively 0.191, 0.308, 0.017, 0.189 and 0.295.

4.2 Deng's similarity approach

Hepu Deng (13) proposed a new approach to find out the best alternative of the multi-criteria decision problem. Deng discovered that, the comparison would be more effective, if magnitude and conflict between the alternative and ideal solution are taken in to consideration. Gradients of the variables indicate the conflicts and from the rank of conflict index, the best alternative can be identified.

Step1: The decision matrix can be established by considering the response characteristics

Step 2: The normalized decision matrix can be found out by determining the normalized value r_{ij} as

$$r_{ij}' = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \qquad \text{Eq. 2}$$

Step 3: The weighted normalized decision matrix can be determined as:

$$V_{Ij} = W_i \, x \, r_{ij} \qquad \text{Eq.3}$$

Step 4: The positive ideal solutions and negative ideal solutions are determined as:

For positive ideal solution, in case of smaller the better, select lowest of column values in case of larger the better, select largest of column values

For negative ideal solution, in case of smaller the better, select largest of column values in case of larger the better, select largest of column values

Step 5: Degree of conflict between each alternative and positive ideal solution and negative ideal solution can calculated as follows:

Conflict between the alternative and positive ideal solution can be obtained as:

$$\cos\theta_i^+ = \frac{\sum_{j=1}^{m} y_{ij}\, y_j^+}{(\sum_{j=1}^{m} y_{ij}^2)^{0.5} (\sum_{j=1}^{m} y_j^{+\,2})^{0.5}} \qquad \text{Eq. 4}$$

$$\cos\theta_i^- = \frac{\sum_{j=1}^{m} y_{ij}\, y_j^-}{(\sum_{j=1}^{m} y_{ij}^2)^{0.5} (\sum_{j=1}^{m} y_j^{-\,2})^{0.5}} \qquad \text{Eq. 5}$$

Step 6: The degree of similarity and conflict between the alternatives and positive and negative ideal solution is calculated as:

$$|C_i| = \cos\theta_i^{+\,-} \times |A_i| \qquad \text{Eq. 6}$$

Degree of similarity

$$S_i^{+\,-} = \frac{|C_i|}{|A^{+\,-}|} = \frac{\cos\theta_i^{+\,-} \times (\sum_{j=1}^{m} y_{ij}^2)^{0.5}}{(\sum_{j=1}^{m} y_j^{+\,-\,2})^{0.5}} \qquad \text{Eq. 7}$$

Step 7: The overall performance index for each alternative is calculate as:

$$P_i = \frac{S_i^+}{S_i^+ - S_i^-} \quad , i = 1,2, \ldots\ldots, n \qquad \text{Eq.8}$$

Step 8: Ranking is done based on descending order with respect to Deng's index

4.3 Analysis of Variance

Analysis of variance (ANOVA) is a method of portioning variability into identifiable sources of variation and the associated degree of freedom in an experiment. The frequency test (F-test) is used in statistics to analyze the significant effects of the parameters which form the response characteristics. The analysis is carried out for a level of significance of 5% ie. 95% level of confidence. The last column in the ANOVA table signifies the "percent" contribution of each factor as the total variation, indicating its influence on the result.

5.0 Results

A series of turning tests were conducted to assess the effect of turning parameters on surface roughness, material removal rate, interface temperature, specific energy and flank wear.the results of experimentation are shown in table.4. Table 5 presents the results related with Deng's method.

5.1 Prediction at optimum levels

The objective of the prediction at optimum levels is to validate the conclusions drawn during the analysis phase. Once the optimal level of process parameters is selected, the next step is to verify the improvement in response characteristics using optimum level of parameters. The predicted values at optimum levels of process parameters is calculated using the following equation:

$$\gamma = \gamma_m + \sum_{i=1}^{n} (\gamma i - \gamma m) \qquad \text{Eq. 9}$$

Where

γ_m is total mean of the required responses

γ_j is the mean of the required responses at optimum level

n is the number of process parameters that significantly affects the multiple performance characteristics

5.2 Confidence interval

Confidence interval is calculated using the formula:

$$C.I = \sqrt{F_{\alpha(1,f_e)} V_e \left(\frac{1}{n_{eff}} + \frac{1}{R}\right)} \qquad \text{Eq. 10}$$

Where f_e = Degrees of freedom for error component

F_α = F-ration from table

$F_{\alpha(1,16)}$ = 4.49 (F-ratio at α = 0.05, 95% confidence level)

V_e = Mean square of error component

N_{eff} = N/(1+ total dof) = 27/(1+10) = 2.4545

5.3 Estimation of confidence interval for Deng's index

The predicted value of Deng's index at optimum level of process parameters (IS1-CF1-V3-F3-d3) is calculated from the equation 9 and is found to be Y_{DI} = 0.7417. A confidence interval of Deng's index on a confirmation run is computed using the Equation 10.

The calculated C.I are + or- 0.0702

The 95% confidence interval of the predicted optimal Deng's index is:

$Y_{DI} - C.I < DI_{expt} < Y_{DI} + C.I$

$0.6715 < DI_{expt} < 0.8119$

The confirmation test is carried-out at optimal setting gives a value of 0.7587 is well with-in confidence interval and hence the optimal setting of process parameters can be implemented. Further the deviation between predicted and experimental value is found to be very low (about 2.29%) hence accepted

Table4. Experimental results of SR, MRR, IT, SE and FW .

Expt No	IS	CF	V	F	d	SR(μm)	MRR (mm^3/sec)	IT (^{0}C)	SE (J/mm^3)	FW (mm)
1	DNMG	CO	100	0.05	0.10	0.268	55.190	35.67	36.445	0.094
2	DNMG	CO	100	0.05	0.15	0.738	80.909	38.67	26.675	0.106
3	DNMG	CO	100	0.05	0.20	1.113	116.664	40.00	19.441	0.118
4	DNMG	PO	150	0.07	0.10	0.336	73.896	38.67	32.177	0.105
5	DNMG	PO	150	0.07	0.15	0.680	138.459	43.67	18.229	0.109
6	DNMG	PO	150	0.07	0.20	0.854	177.686	45.60	14.823	0.113
7	DNMG	GO	200	0.09	0.10	0.184	206.897	37.00	14.145	0.012
8	DNMG	GO	200	0.09	0.15	0.452	263.404	38.25	11.666	0.023
9	DNMG	GO	200	0.09	0.20	0.596	349.252	39.33	9.112	0.052
10	TNMG	CO	150	0.09	0.10	0.232	126.373	37.40	19.394	0.051
11	TNMG	CO	150	0.09	0.15	0.582	180.543	42.00	14.791	0.068
12	TNMG	CO	150	0.09	0.20	0.682	260.220	44.00	10.824	0.101
13	TNMG	PO	200	0.05	0.10	0.432	114.151	35.60	24.035	0.042
14	TNMG	PO	200	0.05	0.15	0.648	158.305	35.75	18.024	0.109
15	TNMG	PO	200	0.05	0.20	0.878	194.311	46.80	15.249	0.113
16	TNMG	GO	100	0.07	0.10	0.322	44.159	43.20	42.248	0.114
17	TNMG	GO	100	0.07	0.15	0.510	60.537	43.40	32.631	0.118
18	TNMG	GO	100	0.07	0.20	0.568	88.332	47.00	24.848	0.145
19	CNMG	CO	200	0.07	0.10	0.567	146.216	33.00	19.765	0.025
20	CNMG	CO	200	0.07	0.15	0.728	216.592	35.25	14.018	0.033
21	CNMG	CO	200	0.07	0.20	1.047	282.822	35.50	11.123	0.061
22	CNMG	PO	100	0.09	0.10	0.334	76.273	41.00	25.419	0.125
23	CNMG	PO	100	0.09	0.15	0.438	111.533	44.00	19.023	0.131
24	CNMG	PO	100	0.09	0.20	0.690	140.177	52.75	15.926	0.140
25	CNMG	GO	150	0.05	0.10	0.448	61.848	42.00	37.854	0.031
26	CNMG	GO	150	0.05	0.15	0.526	105.896	43.30	23.489	0.063
27	CNMG	GO	150	0.05	0.20	0.700	135.025	44.00	19.235	0.082

Table 5.Degree of similarity and ranking of alternatives.

SNo	IS	CF	V	F	d	Deng's index, P	Rank
1	DNMG	CO	100	0.05	0.10	0.2861	25
2	DNMG	CO	100	0.05	0.15	0.3157	22
3	DNMG	CO	100	0.05	0.20	0.3524	19
4	DNMG	PO	150	0.07	0.10	0.3166	21
5	DNMG	PO	150	0.07	0.15	0.4148	16
6	DNMG	PO	150	0.07	0.20	0.4515	12
7	DNMG	GO	200	0.09	0.10	0.7177	1
8	DNMG	GO	200	0.09	0.15	0.6959	2
9	DNMG	GO	200	0.09	0.20	0.6826	3
10	TNMG	CO	150	0.09	0.10	0.5155	9
11	TNMG	CO	150	0.09	0.15	0.5297	8
12	TNMG	CO	150	0.09	0.20	0.5617	6
13	TNMG	PO	200	0.05	0.10	0.4748	10
14	TNMG	PO	200	0.05	0.15	0.4420	13
15	TNMG	PO	200	0.05	0.20	0.4663	11
16	TNMG	GO	100	0.07	0.10	0.2422	27
17	TNMG	GO	100	0.07	0.15	0.2731	26
18	TNMG	GO	100	0.07	0.20	0.3080	24
19	CNMG	CO	200	0.07	0.10	0.5483	7
20	CNMG	CO	200	0.07	0.15	0.6044	4
21	CNMG	CO	200	0.07	0.20	0.5902	5
22	CNMG	PO	100	0.09	0.10	0.3113	23
23	CNMG	PO	100	0.09	0.15	0.3685	18
24	CNMG	PO	100	0.09	0.20	0.3906	17
25	CNMG	GO	150	0.05	0.10	0.3551	20
26	CNMG	GO	150	0.05	0.15	0.4217	15
27	CNMG	GO	150	0.05	0.20	0.4365	14

Table 6. Response table for Deng's method.

Process parameters	Average overall performance index				
	Level 1	Level2	Level 3	Max-Min	Rank
Insert style	0.4704*	0.4241	0.4474	0.0463	5
Cutting fluid	0.4782*	0.4045	0.4592	0.0738	3
Cutting speed(V)	0.3164	0.4448	0.5807*	0.2624	1
Feed (F)	0.3949	0.4166	0.5304*	0.1355	2
Depth of cut(d)	0.4190	0.4518	0.4711*	0.0521	4
*Optimum levels					

6. CONCLUSIONS

1. The optimal parameters setting lies at DNMG insert style, Castor oil cutting fluid, 200 m/min cutting speed, 0.09 mm/rev and 0.20 mm depth of cut. The optimum predicted value for surface roughness is 0.800 µm, MRR 336.822 mm^3/sec, interface temperature 37.222^{0}C, specific energy 3.446 J/mm^3, Flank wear 0.049 mm and Deng's index is 0.7417. Also the experimental value for surface roughness is 0.754 µm, MRR is 345.546 mm^3/sec, interface temperature 35.52^{0}C, specific energy 3.355 J/mm^3, Flank wear 0.045 mm and Deng's index is 7587.
2. It is found that both predicted and experimental response characteristics are significantly better as compared to initial machining parameters. To be specific predicted MRR (336.822 mm^3/sec) and experimental MRR(345.546 mm^3/sec) are much higher as compared to MRR at initial setting level(55.190 mm^3/sec) which paves way for higher production
3. Also predicted specific energy (3.446J/mm^3) and experimental specific energy(3.355 J/mm^3) are much lower than initial setting(36.445 J/mm^3) which is highly expected for reduced machine vibration as also reduced power consumption. Also predicted flank wear(0.049 mm) and experimental flank wear(0.045 mm) are much lower as compared to the initial setting(0.094 mm) which signifies that wear is minimal which increases tool life. It may be noted that there is a good agreement between the predicted Deng's index (0.7417) and experimental Deng's index (0.7587) and therefore the condition **IS1-CF1-V3-F3-d3** of process parameters combination was tested as optimal. Further significant improvement in machinability is observed and measured that there is substantial improvement in MRR (both Experimental value and predicted) and effective improvement in specific energy (Experimental value and predicted value) as compared with initial machining parameters. This encourages applying Deng's similarity approach for optimizing multi response problems.
4. Further, from Analysis of variance (ANOVA) depicts that cutting speed is the most significant parameter followed by feed affecting multi response characteristics with cutting speed 66.55%, feed 20.32% ,cutting fluid 5.67% and depth of cut and insert style almost negligible.
5. The confirmation test is carried-out at optimal setting gives a value of 0.7587 is well with-in confidence interval and hence the optimal setting of process parameters can be implemented.

Table 7. ANOVA based on Deng's method.

Source of variation	Degrees of freedom	Sum of squares	Mean sum of squares	F-ratio	Percent contribution
Insert style	2	0.00979	0.00490	6.2367	2.082
Cutting fluid	2	0.02671	0.01336	16.999	5.674
Cutting speed	2	0.31333	0.15666	199.414	66.555
Feed	2	0.09570	0.04785	60.909	20.324
Depth of cut	2	0.01267	0.00634	8.064	2.691
Error	16	0.01257	0.00078		2.670
`	26				100.000

Table 8. Comparison of predicted and Experimental results using Deng's method.

	Optimum process parameters		
	Initial process parameters	Predicted values	Experimental values
Level of parameters setting	IS1-CF1-V1-F1-D1	IS1-CF1-V3-F3-d3	IS1-CF1-V3-F3-d3
Surface roughness (µm)	0.268	0.800	0.754
MRR (mm^3/sec)	55.190	336.822	345.546
Interface temperature(^{o}C)	35.67	37.22	35.52
Specific energy(J/mm^3)	36.445	3.446	3.355
Flank wear (mm)	0.094	0.049	0.045
Deng's Index	0.2861	0.7417	0.7587

6. Since percentage deviation between experimental performance index and predicted performance index is 2.29%, it is concluded that the adequacy of the model can be accepted.

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