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A Strategic Experimentation Towards Multi Objective Optimization during Turning of Hardened Tool Steel using Taguchi Integrated with Deng's Similarity Approach

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ABSTRACT

Environmental and Ecological issues call for the reduction in usage of cutting fluids in metal cutting industry. New techniques are being inquired to achieve this objective. Hard turning with minimum quantity lubrication is one such technique which can alleviate the pollution problems associated with cutting fluids. In the present work, vegetable oil based cutting fluids like castor oil, palm oil and ground nut oil is made to drop at tool-work interface using over-head system. The present paper deals with experimental investigation carried out for machinability study of hardened AISI D3 steel in combination with CVD coated cemented carbide inserts of different styles and to obtain optimum process parameters using Deng's similarity approach. An orthogonal array, overall performance index and analysis of variance (ANOVA) are applied to study the performance of process parameters such as insert style, cutting fluid cutting speed, feed and depth of cut with consideration of quality characteristics i.e., surface roughness, material removal rate and specific energy. Finally a clear presentation is made for Deng's approach.

1.0 Introduction

The important goal in the modern industries is to manufacture the product with lower cost and with high quality in short span of time. There are two main practical problems that engineers face in a manufacturing process, the first is to determine the product quality (meet technical specifications) and the second is to maximize manufacturing system performance using the available resources. The challenge of modern machining industry is mainly focused on achievement of high quality ,in terms of work piece dimensional accuracy, surface finish ,high production rate, less wear on the cutting tools ,economy of machining in terms of cost saving and increase the performance of the product 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. The primary function of cutting fluid is to reduce interface temperature between tool and work thus tool lip will be extended. Secondary cutting fluid acts as good lubricant by which heat generated due to friction will be reduced. To conclude with high lubricant capacity are suitable in low speed machining such as screw cutting, broaching, gear cutting and difficult to cut materials whereas cutting fluids with high cooling ability are generally employed in high speed machining. 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 Overall performance 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, material removal rate and specific energy.

2.0 Literature Review

.H.Yang & Y.S Tang [1] envisages that the Taguchi method is a powerful tool to design optimization for quality and is used to find the optimal cutting parameters for turning operations. An orthogonal array , the signal to noise ratios and ANOVA are employed to investigate the cutting characteristics of S45C steel bars using Tungsten carbide cutting tools. Through this study, not only optimal cutting parameters for turning operations obtained, but also the main cutting parameters that affect the cutting performance in turning operations are found.

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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 di 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 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. Al2O3/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

In the present study, three turning parameters were selected with three levels as shown in Table.1.

Table 1. 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

Table 2. Process parameters and their levels

Turning parameters	Level 1	Level 2	Level 3
Insert style	DNMG	TNMG	CNMG
Cutting fluid	Castor oil	Palm oil	Ground nut oil
Cutting speed, V(m/min)	100	150	200
Feed, F(mm/rev)	0.05	0.07	0.09
Depth of cut, D(mm)	1.0	1.5	2.0

The experimentation was carried out using L27 orthogonal array based on Taguchi design of experiments. The work material selected for this experiment is hardened AISI D3 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

The turning tests were carried out on Kirloskar model centre lathe machine to determine the responses characteristics for various runs of experiment.

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

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

$$MRR=[\pi/4(D_1^2-D_2^2)L]/t \ mm^3/sec \quad (1)$$

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. Power consumed is measured by using Watt meter fitted to lathe machine.

Table 3. Experimental condition

Machine used	Turn master 35 conventional lathe,
power:	5 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	PDJNR2020M15WIDAX, MTJNR 2020K16 WIDAX, PCLNR2020K12 V tool
Cutting insert	DNMG150608EN-TMR, T NMG160408 EN- TM,
	CNMG 120408 EN- TMR
MQL supply	Castor oil, Palm oil and ground nut
	oil (300 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	1.0-2.0 mm
Response variables	Surfaceroughness,SR(µm),Materialremoval rate MRR(mm3/sec),andSpecificenergy, SE(J/mm^3)

Table 3. Process parameters and their levels

Turning parameters	**Level 1**	**Level 2**	**Level 3**
Insert style	DNMG	TNMG	CNMG
Cutting fluid	Castor oil	Palm oil	Ground nut oil
Cutting speed, V(m/min)	100	150	200
Feed, F(mm/rev)	0.05	0.07	0.09
Depth of cut, D(mm)	1.0	1.5	2.0

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 and W_3 are weights assigned to the Ra, MRR and SE, W_{Ra} = 0.278, W_{MRR} = 0.447 & W_{SE} = 0.275

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

$$r_{ij}^{'} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (2)$$

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

$$V_{ij} = W_i \, x \, r_{ij} \quad (3)$$

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:

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

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

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

$$|C_i| = \cos\theta_i^{+-} \times |A_i| \quad (6)$$

Degree of similarity

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

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

$$P_i = \frac{S_i^+}{S_i^+ - S_i^-} \quad , i = 1,2,\dots\dots\dots,n \quad (8)$$

Step 8: Ranking is done based on descending order with respect to overall performance 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.

Table 4. Experimental data and results for 3 parameters, corresponding Ra, MRR and Specific energy for CVD tool

Expt No	Insert Style	Cutting fluid	Cutting speed(m/min)	Feed (mm/rev)	Doc(mm)	Surface roughness(μm)	Material removal rate(mm^3/sec)	Specific Energy (j/mm^3)
1	DNMG	CO	100	0.05	1.0	0.268	55.190	36.445
2	DNMG	CO	100	0.05	1.5	0.738	80.909	26.675
3	DNMG	CO	100	0.05	2.0	1.113	116.664	19.441
4	DNMG	PO	150	0.07	1.5	0.336	73.896	32.177
5	DNMG	PO	150	0.07	2.0	0.680	138.459	18.229
6	DNMG	PO	150	0.07	1.0	0.854	177.686	14.823
7	DNMG	GO	200	0.09	2.0	0.184	206.897	14.145
8	DNMG	GO	200	0.09	1.0	0.452	263.404	1.666
9	DNMG	GO	200	0.09	1.5	0.596	349.252	9.112
10	TNMG	CO	150	0.09	1.0	0.232	126.373	19.394
11	TNMG	CO	150	0.09	1.5	0.582	180.543	14.791
12	TNMG	CO	150	0.09	2.0	0.682	260.220	10.824
13	TNMG	PO	200	0.05	1.0	0.432	114.151	24.035
14	TNMG	PO	200	0.05	1.5	0.648	158.305	18.024
15	TNMG	PO	200	0.05	2.0	0.878	194.311	15.249
16	TNMG	GO	100	0.07	1.0	0.322	44.159	42.248
17	TNMG	GO	100	0.07	1.5	0.510	60.537	32.631
18	TNMG	GO	100	0.07	2.0	0.568	88.332	24.848
19	CNMG	CO	200	0.07	1.0	0.567	146.216	19.765
20	CNMG	CO	200	0.07	1.5	0.728	216.592	14.018
21	CNMG	CO	200	0.07	2.0	1.047	282.822	11.123
22	CNMG	PO	100	0.09	1.0	0.334	76.273	25.419
23	CNMG	PO	100	0.09	1.5	0.438	111.533	19.023
24	CNMG	PO	100	0.09	2.0	0.690	140.177	15.926
25	CNMG	GO	150	0.05	1.0	0.448	61.848	37.854
26	CNMG	GO	150	0.05	1.5	0.526	105.896	23.489
27	CNMG	GO	150	0.05	2.0	0.700	135.025	19.235

Table 5. Degree of conflicts of the alternatives

Expt No	Normalized values			Weighted Normalized values			Degree of conflicts		C+	C-
	SR	MRR	Specific energy	SR	MRR	Specific energy	COSθ+	COSθ-		
1	0.0835	0.0642	0.3073	0.0232	0.02871	0.08506	0.43369	0.86900	0.04021	0.08058
2	0.2299	0.0941	0.2249	0.0639	0.04208	0.06185	0.55199	0.96178	0.05431	0.09462
3	0.3860	0.1357	0.1639	0.1073	0.06068	0.04507	0.56799	0.88321	0.07455	0.11592
4	0.1047	0.0859	0.2713	0.0291	0.03844	0.07461	0.55332	0.88838	0.04915	0.07892
5	0.2118	0.1611	0.1537	0.0589	0.07202	0.04226	0.79504	0.80569	0.08125	0.08234
6	0.2661	0.2068	0.1249	0.0739	0.09242	0.03437	0.12428	0.73462	0.01532	0.09052
7	0.0573	0.2407	0.1193	0.01594	0.10761	0.03279	0.98262	0.45604	0.11164	0.05182
8	0.1408	0.3065	0.0983	0.03915	0.13701	0.02705	0.97967	0.47356	0.14209	0.06868
9	0.1857	0.4064	0.0768	0.05163	0.18165	0.02112	0.98234	0.42366	0.18667	0.08051
10	0.0722	0.1470	0.1635	0.02009	0.06573	0.04497	0.87614	0.68600	0.07196	0.05635
11	0.1814	0.2101	0.1247	0.0504	0.09391	0.03429	0.90436	0.66499	0.10125	0.07445
12	0.1957	0.3028	0.0913	0.0544	0.13535	0.02509	0.95630	0.52416	0.14155	0.07758
13	0.1346	0.1328	0.2027	0.03742	0.05937	0.05573	0.76341	0.83525	0.06841	0.07485
14	0.2019	0.1842	0.1519	0.05614	0.08234	0.04179	0.84361	0.75686	0.09116	0.08179
15	0.2736	0.2261	0.1286	0.07605	0.10106	0.03536	0.84275	0.71676	0.11068	0.09413
16	0.1003	0.0514	0.3562	0.02789	0.02297	0.09796	0.34887	0.88059	0.03643	0.09194
17	0.1589	0.0704	0.2751	0.04418	0.03148	0.07566	0.46934	0.95535	0.04329	0.08894
18	0.1769	0.1028	0.2095	0.04921	0.04594	0.05760	0.63615	0.92675	0.05636	0.08211
19	0.1767	0.1701	0.1667	0.04912	0.07605	0.04583	0.83564	0.77590	0.08479	0.07874
20	0.2269	0.2520	0.1182	0.06306	0.11266	0.03250	0.90657	0.63881	0.12069	0.08504
21	0.3263	0.3291	0.0937	0.09069	0.14711	0.02579	0.89518	0.60162	0.15642	0.10512
22	0.1041	0.0887	0.2143	0.0289	0.03967	0.05894	0.63297	0.88613	0.04855	0.06797
23	0.1365	0.1298	0.1604	0.0379	0.05801	0.04411	0.80071	0.81312	0.06577	0.06679
24	0.2150	0.1630	0.1343	0.05977	0.07288	0.03693	0.80567	0.78361	0.08156	0.07933
25	0.1396	0.0719	0.3192	0.0388	0.03217	0.08777	0.44762	0.92721	0.4531	0.09385
26	0.1639	0.1232	0.1981	0.0455	0.05508	0.05446	0.72048	0.87765	0.06472	0.07884
27	0.2181	0.1571	0.1622	0.06064	0.07023	0.04460	0.77605	0.82450	0.07989	0.08488

Table 6. Degree of similarity and ranking of alternatives

SNo	Insert style	Cutting fluid	Cutting speed	Feed	Depth of cut	S+	S-	P	Rank
1	DNMG	CO	100	0.05	1.0	0.21906	0.57821	0.27477	23
2	DNMG	CO	100	0.05	1.5	0.29583	0.67901	0.30347	22
3	DNMG	CO	100	0.05	2.0	0.40610	0.83183	0.32805	20
4	DNMG	PO	150	0.07	1.5	0.26775	0.56629	0.32103	21
5	DNMG	PO	150	0.07	2.0	0.44258	0.59082	0.42827	13
6	DNMG	PO	150	0.07	1.0	0.08343	0.64957	0.11381	27
7	DNMG	GO	200	0.09	2.0	0.60816	0.37181	0.62059	2
8	DNMG	GO	200	0.09	1.0	0.77402	0.49286	0.61096	3
9	DNMG	GO	200	0.09	1.5	1.01688	0.57772	0.63770	1
10	TNMG	CO	150	0.09	1.0	0.39201	0.40432	0.49227	8
11	TNMG	CO	150	0.09	1.5	0.55155	0.53426	0.50796	7
12	TNMG	CO	150	0.09	2.0	0.77106	0.55673	0.58071	4
13	TNMG	PO	200	0.05	1.0	0.37267	0.53712	0.40962	16
14	TNMG	PO	200	0.05	1.5	0.49660	0.58691	0.45833	10
15	TNMG	PO	200	0.05	2.0	0.60289	0.67546	0.47162	9
16	TNMG	GO	100	0.07	1.0	0.19843	0.65971	0.23121	26
17	TNMG	GO	100	0.07	1.5	0.23802	0.63823	0.27164	24
18	TNMG	GO	100	0.07	2.0	0.30702	0.58920	0.4258	19
19	CNMG	CO	200	0.07	1.0	0.46191	0.56499	0.44981	11
20	CNMG	CO	200	0.07	1.5	0.65743	0.61025	0.51861	6
21	CNMG	CO	200	0.07	2.0	0.85205	0.75434	0.53042	5
22	CNMG	PO	100	0.09	1.0	0.26446	0.48771	0.35159	18
23	CNMG	PO	100	0.09	1.5	0.35828	0.47928	0.42777	14
24	CNMG	PO	100	0.09	2.0	0.44428	0.56923	0.43836	12
25	CNMG	GO	150	0.05	1.0	0.24679	0.67342	0.26819	25
26	CNMG	GO	150	0.05	1.5	0.35257	0.56575	0.38393	17
27	CNMG	GO	150	0.05	2.0	0.43521	0.60910	0.41675	15

Table 7. Response table for Deng's similarity approach

Process parameters	Average overall performance index				
	Level 1	Level2	Level 3	Max-Min	Rank
Insert style	0.4043	0.4186	0.4206*	0.0163	5
Cutting fluid	0.4431*	0.3800	0.4204	0.0630	3
Cutting speed(V)	0.3299	0.3905	0.5231*	0.1931	1
Feed (F)	0.3683	0.3564	0.5189*	0.1625	2
Depth of cut(D)	0.3799	0.4347*	0.4289	0.0548	4
Total mean value of the overall performance index = 0.4145 *Optimum levels					

Table 8. ANOVA based on Deng's similarity approach

Source of variation	Degrees of freedom	Sum of squares	Mean sum of squares	F-ratio	Percent contribution
Insert style	2	0.00141	0.000706	0.1612	0.3292
Cutting fluid	2	0.01825	0.009128	2.0853	4.2559
Cutting speed	2	0.17571	0.087855	20.071	40.9658
Feed	2	0.14725	0.073625	16.820	34.3306
Depth of cut	2	0.01625	0.008128	1.8570	3.79015
Error	16	0.07004	0.004377		16.3280
`	26				100.0000

Table 9. Comparison of predicted and Experimental results using Deng's similarity approach

	Optimum process parameters		
	Initial process parameters	**Predicted values**	**Experimental values**
Level of parameters setting	S1-CF1-V1-F1-D1	S3-CF1-V3-F3-D2	S3-CF1-V3-F3-D2
Surface roughness (μm)	0.268	0.6317	0.6612
MRR (mm^3/sec)	55.190	268.568	279.572
Specific energy(J/mm^3)	36.445	5.944	9.325
Performance index	0.27477	0.6823	0.6509

5.0 Results

A series of turning tests were conducted to assess the effect of turning parameters on surface roughness and material removal rate and the results of experimentation are shown in table.4. Tables 5,6,7,8 and 9 depicts the results related with Deng's similarity approach.

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. A conformity test is conducted using the following equation:

$$\gamma = \gamma_m + \sum_{i=1}^{n}(\gamma i - \gamma m) \quad (9)$$

Where γm is total mean of the required responses

γj is the mean of the required responses at optimum level

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

6. Conclusions

1. The optimal parameters setting lies at CNMG insert style, Castor oil cutting fluid, 200 m/min cutting speed, 0.09 mm/rev and 1.5 mm depth of cut. The optimum predicted value for surface roughness is 0.6317 µm, MRR 268.568 mm^3/sec, specific energy 5.944 J/mm^3, and performance index is 0.6823. Also the experimental value for surface roughness is 0.6612 µm, MRR is 279.572 mm^3/sec and specific energy 9.325 J/$mm^3$and performance index is 6509.
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 (268.568 mm^3/sec) and experimental MRR(279.572 mm^3/sec) are much higher as compared to MRR at initial setting level which paves way for higher productivity. Also predicted specific energy (5.944 J/mm3) and experimental specific energy(9.325 J/mm3) are much lower than initial setting which is highly expected for reduced machine vibration as also reduced power consumption. It may be noted that there is a good agreement between the predicted performance index (0.6823) and experimental performance index (0.6509) and therefore the condition **S3-CF1-V3-F3-D2** 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.
3. 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 40.965%, feed 34.331% ,cutting fluid 4.255% and depth of cut and insert style almost negligible.
4. Since percentage deviation between experimental performance index and predicted performance index is 4.7%, it is concluded that the adequacy of the model can be accepted

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