EXPERIMENTAL EVALUATION FOR MULTI-RESPONSE OPTIMALITY ON AISI 316 L MATERIALS WITH COATED CARBIDE INSERTS USING GRA AND VIKOR METHODS

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ABSTRACT

Experimental evaluations are prominent in metal cutting industries, as they predict the real time analysis of the machining. This work relates in experimental optimal analysis of machining parameters using Grey Relational Analysis (GRA) and VIKOR methods on surface roughness, tool temperatures and metal removal rate while machining on CNC lathe. A comparison on multi-objective optimal analysis between GRA and VIKOR is carried. Study on AISI 316L work piece materials have been considered under dry machining with spindle speed, feed and depth of cut as machining parameters. Analysis of Variance was used to evaluation of predominance of machining parameters. In this paper, the novelty of utilization of VIKOR method comparable to GRA, which was attempted only for supply chain problems and was successfully adopted for machining optimization. The VIKOR method shows giving due weight to all machining parameters results in exactness of multi-response decision optimization, which was not present in GRA method.

KEYWORDS: GRA, Metal Removal Rate, Roughness, Tool Temperature & VIKOR

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1. INTRODUCTION

The basic areas of evaluations in metal cutting processes are surface finish, temperature generations and metal removal rate. These evaluations can be done either analytically or experimentally. The analytical methods perform well accurately in assumptions and static conditions, inexpensive but are tedious. On the other hand, experimental methods are easy to adopt if having expertise over the measuring equipment, gives accurate and precise true picture, and can be helpful for static and dynamic states.

Manufacturing deeply involves in indentifying the optimal combination of machining parameters to reduce the production and process costs. So, optimal techniques have gained much of their importance. The optimal technique reported till now are of either numerical which gives exact optimal solutions or heuristic methods which gives near optimal solutions. In the present work, numerical methods like Grey Relational Analysis (GRA) and VIKOR, which normalize the combination of qualitative and quantitative criteria are adopted for multi-response optimality determination.

Taguchi's concept of optimization is a bench mark point for all manufacturing optimization, but lags in solving multi-objective optimization, and so, numerical methods like Grey relational analysis (GRA), VIKOR, TOPSIS etc can be integrated with Taguchi method for this purpose (Khalilpourazary et al, 2014; Lal S et al, 2013).

Researcher like Elanchezhian et al, (2010) attempted the analytic network process and TOPSIS for vendor selection process. Similarly, Kassaei et al, (2013) reported a hybrid MCDM integrated model using fuzzy analytic network process and fuzzy TOPSIS for vendor selection by giving weights. Alireza Anvari et al, (2014) attempted modifying VIKOR method for applying it for decision-making problems in lean tool selection. Ali Jahan et al, (2011) and Tara Sasanka et al, (2015) researched on developing better material selection in biomedical and automotive applications, respectively.

Multi-response/criteria decision making technique like VIKOR has been less concentrated for application over manufacturing processes, but concentrated on solving supplier selection problems only, hence added a novelty to this work. Apart from it, GRA depends on simple and vague weight age of responses under consideration, while VIKOR adopts weight age of each response individually for optimal determination. In this paper, experimental investigation of surface finish/roughness (R_a), tool temperature (T) and metal removal rate (MRR) was considered for study while machining AISI 316L stainless steel cylindrical work piece for optimal studies. Taguchi Design of experiments (TDOE) with orthogonal array concept with L16 combination of experiments is taken as experimental design while turning under dry conditions with coated carbide inserts.

2. MATERIAL TOOLS AND EQUIPMENT USED

Stainless steels have corrosion resistance and contain minimum of 0.10% chromium. Stainless steels with austenitic structures have hardness, not a guide for speeds. American Iron and Steel Institute (AISI) 316L grade is similar to AISI 304 (chromium-nickel stainless steel) but has an addition element like molybdenum, which increases creep strength, hot hardness, corrosion resistance, wear resistance and deepens hardening. The chemical composition of AISI 316L includes Cr 17.5%, C 0.06%, Mn 1.5%, Ni 12.2%, Mo 2.5%, Si 0.75% and remaining Fe. The work piece materials with 30mm diameter and 100mm long are shown in fig.1.1a. K-type shielded thermocouple was used for recording tool temperature, while MITUTOYO surface roughness tester was used to measure surface roughness parameters, as shown in fig.1.1a. Physical Vapour Deposition (PVD) TiAlN Coated carbide inserts with KC 5010 grade are used for enhanced speed machining and for short chipping. The coated carbide inserts of CNMG120408 MS KC 5010 are used for machining on ACE Micromatic CNC lathe with Fanuc 0i control system, shown in fig.1.1b.

Figure 1.1.a: AISI 316L Work Piece after Machining and Surface Roughness Tester SJ-301

Figure 1.1.b: CNC Lathe with Fanuc-0i Control System and Coated Carbide Inserts

3. MACHINING PROCESS AND METHODOLOGY

Experimental design of L_{16} using Taguchi orthogonal array concept, as shown in Table 1 is used for machining on AISI 316L work piece. Each design was experimented using a new coated carbide insert tip for avoiding tool wear, under dry conditions. Machining parameters viz. Spindle speed (N-1300, 1500, 1700, 1900 rpm), feed (f- 0.10, 0.14, 0.18, 0.22 mm/rev) and depth of cut (d- 0.3, 0.6, 0.9, 1.2 mm) are considered for machining with four levels each. Responses like average surface roughness (R_a) and tool temperature (T) were measured using surface roughness tester and thermostat respectively, while the metal removal rate (MRR) was calculated theoretically, as given in Table 1.

The obtained responses were used to analyse the significances of parameters using Analysis of variance (ANOVA) and also were used to evaluate multi-objective optimization criteria using numerical techniques like Gray relational analysis (GRA) and VIKOR. At the end, both these methods were compared for their effective utilization.

Table 1: Experimental Design and Responses Observation Values

Exp No	Speed (rpm)	Feed (mm/rev)	Depth of cut (mm)	R_a (μ m)	Tool Temperature ($^{\circ}$ C)	MRR (mm^3/min)
1	1300	0.10	0.3	0.723	66	3637
2	1300	0.14	0.6	1.103	69	10081
3	1300	0.18	0.9	1.727	77	19243
4	1300	0.22	1.2	2.890	83	31036
5	1500	0.10	0.6	0.577	77	8308
6	1500	0.14	0.3	1.077	70	5875
7	1500	0.18	1.2	1.317	84	29300
8	1500	0.22	0.9	2.507	78	27138
9	1700	0.10	0.9	0.793	77	13980
10	1700	0.14	1.2	0.953	83	25827
11	1700	0.18	0.3	1.653	58	8561
12	1700	0.22	0.6	2.063	62	20716
13	1900	0.10	1.2	0.603	83	20618
14	1900	0.14	0.9	0.610	80	21875
15	1900	0.18	0.6	1.777	68	18943
16	1900	0.22	0.3	2.193	54	11695

3.1.1. Grey Relational Analysis (GRA)

GRA is a multi-response optimization technique, which generates an optimal process parameter combination for all the responses generated by normalizing response values for making them comparable. Thereby, determining the gray relation grade based on the deviation of normalized values and ranking the highest grade, as optimal. It was proposed by Deng (Ahilan et al, 2010; Jayaraman et al, 2014; Pankaj Sharma et al, 2013) and has been proven to be useful for dealing with the problems with poor, insufficient and uncertain information.

Step 1: Normalization of experimental response data to convert into a sequence of comparable data using equation-1:

Response with low noise like surface finish and temperatures adopts;

$$\text{Lower-is-Better (LB): } x_i^*(j) = \frac{[\max(x_i(j)) - x_i(j)]}{[\max(x_i(j)) - \min(x_i(j))]} \quad (1a)$$

Response with high noise like metal removal rate adopts;

$$\text{Higher-is-Better (HB): } x_i^*(j) = \frac{[x_i(j) - \min(x_i(j))]}{[\max(x_i(j)) - \min(x_i(j))]} \quad (1b)$$

Where, $X_i(j)$ is value of response of i^{th} experiment, $\max(x_i(j))$ and $\min(x_i(j))$ are the smallest and largest values of $X_i(j)$, respectively.

Sample Calculation for Surface Roughness

Experiment Number 1

For Normalization, Lower-is-Better (LB) and using the Equation: 1a, we get

$$\text{For Lower-is-Better (LB): } x_i^*(j) = \frac{[\max(x_i(j)) - x_i(j)]}{[\max(x_i(j)) - \min(x_i(j))]} = [(2.98 - 0.723) / (2.98 - 0.577)] = 0.9392$$

$$\text{Step 2: The deviation sequence } \Delta_{oi}(k) \text{ of each response given as: } \Delta_{oi}(k) = \|X_o(k) - X_i(k)\| \quad (2)$$

$$\text{The deviation sequence using Equation: 2: } \Delta_{oi}(k) = \|X_o(k) - X_i(k)\| = |0.9392 - 1| = 0.0608$$

Step 3: Grey relational coefficient correlation between responses by giving equal weight age (distinguishable coefficient) as given in equation-3.

$$\gamma_i = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{oi}(k) + \zeta \Delta_{\max}} \quad (3)$$

Where, $\Delta_{\min}$ is smallest value of the normalized values, $\Delta_{\max}$ is maximum value of the normalized values, ζ is distinguishing coefficient and ranges from 0 to 1 and had been assumed as 0.5 (Khalilpourazary et al, 2014).

Grey relational coefficient is calculated using Eq: 3 and is given in Table 2a, as

$$\gamma_i = ((0 + 0.5 * 1) / ((0.0608 + (0.5 * 1)))) = 0.892$$

Step 4: Determination of grey relational grade of combined responses as given in Equation-4 and are graded as optimal with highest rank, as shown in Table 2a:

$$\alpha_i = \frac{1}{n} \sum_{k=1}^n \gamma_i(k) \quad (4)$$

Where, “ n_r ” is total number of responses

Basing on the grey relational grade, the ranking has to be given in descending order. The combination of process parameters, which has highest rank is considered to be optimal, as given in Table 2a. Grey relational grade using Equation-4 and are graded as optimal with highest rank: $\alpha_1 = \frac{(0.892 + 0.333 + 0.556)}{3} = 0.594$

Table 2a: Normalization, Grey relational Coefficient for Determining
Grey Relational Grade and Ranking

Exp. No	Normalization based on LB/HB			Grey Relational Coefficients			Grey Relational Grade	Rank
	Ra (μm)	MRR (mm ³ /min)	Temp (Degree)	Ra (μm)	MRR (mm ³ /min)	Temp (Degree)		
1	0.9392	0.0000	0.6000	0.892	0.333	0.556	0.594	
2	0.7811	0.2352	0.5000	0.696	0.395	0.500	0.530	
3	0.5214	0.5696	0.2333	0.511	0.537	0.395	0.481	
4	0.0000	1.0000	0.0333	0.333	1.000	0.341	0.558	
5	1.0000	0.1705	0.2333	1.000	0.376	0.395	0.590	
6	0.7919	0.0817	0.4667	0.706	0.353	0.484	0.514	
7	0.6921	0.9366	0.0000	0.619	0.888	0.333	0.613	
8	0.1968	0.8577	0.2000	0.384	0.778	0.385	0.516	
9	0.9101	0.3775	0.2333	0.848	0.445	0.395	0.563	
10	0.8435	0.8099	0.0333	0.762	0.725	0.341	0.609	
11	0.5522	0.1797	0.8667	0.528	0.379	0.789	0.565	
12	0.3816	0.6233	0.7333	0.447	0.570	0.652	0.557	
13	0.9892	0.6198	0.0333	0.979	0.568	0.341	0.629	
14	0.9863	0.6656	0.1333	0.973	0.599	0.366	0.646	1
15	0.5006	0.5586	0.5333	0.500	0.531	0.517	0.516	
16	0.3275	0.2941	1.0000	0.426	0.415	1.000	0.614	

3.1.2. VIKOR Method

VIKOR method, developed by a Serbian, named Zeleny is useful in generating solution for multi-response/criteria decision making problems by identifying solutions that are closer to the ideal solution and farther from the negative-ideal solution. This method adopts maximizing the utilization set and minimizing regret set. This methods helps in providing conflicting and non-commensurable criteria solution for multi-criteria decision making problems, when the decisions close to ideal solution are required by assuming acceptability for conflict resolution (Suresh and Narayana rao, 2018).

Step 1: The response experimental data has to be normalized for comparing between them using equation-5:

The normalized decision matrix can be expressed as follows: $F = [f_{ij}]_{m \times n}$ (5)

Where, $f_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^n x_{ij}^2}}$, $i=1,2,\dots,m$; $j=1,2,\dots,n$; x_{ij} is the performance of alternative A_j with respect to the

j^{th} criterion, as shown in Table 2b.

Sample Calculation for Surface Roughness

Experiment Number 1

For Normalization decision matrix, using the Equation: 5, we get: $f_{11} = \frac{70}{\sqrt{66^2 + 0.723^2 + 3637^2}} = 0.01814$

Table 2b: Normalized Decision Matrix of Response Values

Exp. No	Normalization of Multi-Response Decisions		
	Temp (Degree)	Ra (μm)	MRR (mm^3/min)
1	0.0181435	0.000199	0.999835
2	0.0068445	0.000109	0.999977
3	0.0040013	0.000090	0.999992
4	0.0026743	0.000096	0.999996
5	0.0092673	0.000069	0.999957
6	0.0119135	0.000183	0.999929
7	0.0028669	0.000045	0.999996
8	0.0028742	0.000092	0.999996
9	0.0055077	0.000057	0.999985
10	0.0032136	0.000037	0.999995
11	0.0067747	0.000193	0.999977
12	0.0029929	0.000100	0.999996
13	0.0040255	0.000029	0.999992
14	0.0036571	0.000028	0.999993
15	0.0035896	0.000094	0.999994
16	0.0046175	0.000188	0.999989

Step 2: Determine positive-ideal solution A^* and negative-ideal solution A^-

$$A^* = \left\{ \left(\max f_{ij} \mid j \in J \right) \text{ or } \left(\min f_{ij} \mid j \in J \right) \mid i = 1, 2, \dots, m \right\} = \{ f_1^*, f_1^*, \dots, f_j^*, \dots, f_n^* \} \quad (6a)$$

$$A^- = \left\{ \left(\min f_{ij} \mid j \in J \right) \text{ or } \left(\max f_{ij} \mid j \in J \right) \mid i = 1, 2, \dots, m \right\} = \{ f_1^-, f_1^-, \dots, f_j^-, \dots, f_n^- \} \quad (6b)$$

From Table 2b, we have $A^* = 0.000028$ and $A^- = 0.000199$, as the smaller is better for surface roughness.

Step 3: Evaluation of Utility (U_i) and Regret (R_i) measure

$$U_i = \sum_{j=1}^n w_j \left[\frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \right] \quad \text{and} \quad R_i = \max_j \left\{ w_j \left[\frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \right] \right\} \quad ; \quad \text{where } w_j = \text{weight of the } j^{\text{th}} \text{ criterion.} \quad (7)$$

Step 4: Determination of VIKOR (V) indices

$$V = v \left[\frac{S_i - S^*}{S^- - S^*} \right] + (1 - v) \left[\frac{R_i - R^*}{R^- - R^*} \right] \quad (8)$$

Where $S^* = \min (S_i)$, $S^- = \max (S_i)$, $R^* = \min (R_i)$, $R^- = \max (R_i)$ and v is the weight of the maximum group utility and its value is usually set to 0.5 (Suresh and Narayana., 2018; Liu., 2016).

Basing on the order of preference, the VIKOR index with low value is treated as optimal, as shown in Table 2c

Table 2c: Weight Age, Utility and Regret Measures of Responses for Determining VIKOR Index and Ranking

Exp. No	Weight Age Calculations			Utility Measure	Regret Measure	VIKOR Indices	Rank
	Temp	Ra	MRR				
1	5.645851155	3.191207627	1.313801552	10.1508603	5.6458512	0.6882	
2	5.902480753	4.868467514	3.641486321	6.6991463	2.7850681	0.3641	
3	6.586826347	7.622704802	6.951204573	6.3165564	2.9918700	0.3595	
4	7.100085543	13.15324859	11.21110657	5.2446233	5.2446233	0.4464	
5	6.586826347	2.546786723	3.00122499	5.9162799	2.8073106	0.3307	
6	5.988023952	4.753707627	2.122294814	9.8490817	4.3237116	0.5958	

7	7.185628743	5.813029661	10.5839118	1.3406655	0.6707052	0.0000	1
Table 2c: Contd.,							
8	6.672369547	11.06550141	9.802980808	5.6575443	4.1766166	0.4010	
9	6.586826347	3.500176554	5.050020416	4.9408224	3.1436447	0.3075	
10	7.100085543	4.206391243	9.329522254	2.2430721	1.7736427	0.1059	
11	4.96150556	7.296080508	3.092486729	10.9055969	7.0537361	0.8057	
12	5.303678358	9.10575565	7.483054308	6.7488785	3.8209765	0.4282	
13	7.100085543	2.66154661	7.447937934	3.4732203	2.8318665	0.2237	
14	6.843455945	2.692443503	7.901796652	3.0768853	2.6420823	0.1948	
15	5.816937553	7.843396893	6.842792977	6.3903177	3.0259484	0.3648	
16	4.619332763	9.679555085	4.224377297	12.6055709	9.0432206	1.0000	

3.1.3. Analysis of Variance

Analysis of variance (ANOVA) is a statistical model, based on hypothesis of accepting or rejecting null hypothesis, by analyzing the difference between groups and among the groups. Based on relation between $F_{\text{statistical}}$ and F_{critical} , the acceptance and rejection of hypothesis is done. The ANOVA uses equations: 9-12 to determine significances and indicates the contribution of design parameters on the quality characteristic of the response with significance level of 95% (i.e. < 0.05 probability) (Arun Vikram et al, 2015) and are shown in Table 3.

$$SS_{\text{Total}} = \sum X^2 - \frac{(\sum X)^2}{N} \text{ and } DF = N - 1 \quad (9)$$

$$SS_{\text{Between}} = \frac{(\sum X_1)^2}{n_1} + \frac{(\sum X_2)^2}{n_2} + \dots + \frac{(\sum X_{AC})^2}{n_{AC}} - \frac{(\sum X)^2}{N} \quad (10)$$

$$SS_{\text{Within}} = SS_{\text{Total}} - SS_{\text{Between}} \quad (11)$$

Where, SS is sum of squares, MS is mean square, “DF” is degree of freedom, N is total observations, n is size of population.

Table 3: ANOVA of Experimental Responses Data

Source	DF	SS	MS	F	P	Remarks
Surface Roughness (R_a) (F-Critical of 3,6 is 4.757)						
Speed (rpm)	3	10.5	3.45	1.02	0.446	Not significant (NS)
Feed (mm/rev)	3	294.60	98.2	29.14	0.001	Highly significant (HS)
d (mm)	3	00.981	0.33	0.10	0.959	Not significant (NS)
Error	6	20.21	3.36			
Tool Temperature (Temp)						
Speed (rpm)	3	2.12	0.707	5.47	0.037	S
Feed (mm/rev)	3	2.14	0.714	5.53	0.037	S
d (mm)	3	16.09	5.365	41.5	0.000	HS
Error	6					
Metal Removal Rate (MRR)						
Speed (rpm)	3	24.17	8.05	143248	0.000	HS
Feed (mm/rev)	3	104.72	34.90	620656	0.000	HS
d (mm)	3	313.23	104.4	185641	0.000	HS
Error	6					

4. RESULTS AND DISCUSSIONS

Observing Table 2a, using GRA, the optimality obtained is Spindle speed: 1900 rpm, feed: 0.14 mm/rev and depth of cut: 0.9 mm, which generates surface roughness ($R_a = 0.610 \mu\text{m}$), Tool temperature (Temp = 80°C) and metal removal rate ($\text{MRR} = 21875 \text{ mm}^3/\text{min}$). Similarly, observing Table 2c, the optimal combination of machining parameters for multi-

object criteria using VIKOR method is Spindle speed: 1500 rpm, feed: 0.18 mm/rev and depth of cut: 1.2 mm, which generates surface roughness ($R_a = 1.317 \mu\text{m}$), Tool temperature ($\text{Temp} = 84^\circ\text{C}$) and metal removal rate ($\text{MRR} = 29300 \text{ mm}^3/\text{min}$). The GRA method generates better result in case of roughness and temperature, but not in case of Metal removal rate. But, if given due weightage of responses are incorporated in GRA, and then optimality may not be better than VIKOR method.

Basing on ANOVA for finding significance of machining parameters, graph plots are drawn between responses and major contributing parameters. As shown in fig. 2, feed indicates much more effective than spindle speed while generating roughness and similarly, depth of cut on tool temperatures and MRR.

Figure 2: Graph Plots of the Results Obtained from TDOE

CONCLUSIONS

- The chips generated in machining are found to be of helix in nature and at higher depth of cuts, they broke into long helical chips due to weight.
- Discontinuous small helical chips were produced at low feeds and depth of cut, while at moderate feed and depth of cuts, helical chips whirled around the work piece from the middle of the machining.
- The multi-objective optimal combination showed in both GRA and VIKOR are not same, as weightage of machining parameters were considered in case of VIKOR, but not in GRA. If due- weightage were given in GRA also, then the optimal combination may be similar to that of VIKOR.
- Analyzing ANOVA of the machining parameters on the generated responses: feed alone constitutes for generating surface roughness, while all the parameters contributes significantly, but depth of cut contributes more significantly in generating tool temperatures due to penetration of tool into work piece, and in case of metal removal rate, all the parameters are highly significant in its generation.

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