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Development of an Artificial Grey Fuzzy Inference System to Optimize Hole Quality and Tool Performance in Drilling

Satya Sai Ravi Kiran Dwibhashyam[1], Balla Srinivasa Prasad[2]

[1]*Assistant Professor, Mechanical Engineering, ANITS, Visakhapatnam, 531162 India*
[2]*Professor, Mechanical Engineering, GIT, GITAM, Visakhapatnam, 530045 India*

[1]sairavikiran.me@anits.edu.in, [2]bsp.prasad@gmail.com

Abstract - *In this work, a sincere effort is made towards developing a fuzzy-based inference model to elevate the performance of drill tool materials (flank wear, VB and temperature, T) and hole quality (Circularity error, C_r). Three different drill bit materials, namely HSS, uncoated tungsten carbide (WC), and coated tungsten carbide (WC), are used to drill holes on the Ti-6Al-4V specimen. Taguchi's L_{25} orthogonal array is operated to draft the conducting order of the experiments. The machining factors like rotational speed (N) and feed rate (f) are optimized by keeping cutting depth constant for mobilizing the outcomes. ANOVA is executed, and it is observed that the rotational speed played the foremost role of feed rate in the ascertainment of tool performance. Affirmation tests are performed to corroborate the outcomes, and it is found that grey-fuzzy methodology remains effective in defining the optimal machining parameters.*

Keywords - *Grey fuzzy inference system, circularity error, flank wear, infrared thermography, drilling.*

I. INTRODUCTION

The machining of titanium is usually painstaking to be meagrely owed to numerous intrinsic material properties. Ti-6Al-4V is chemically responsive. Hence, it inclines to fuse to the cutting tool while cutting, leading to chippings and early tool let down. It is found that "machining of titanium alloys would continuously be problematic, irrespective of what methods are employed to transmute this metal into chips [1]." The machining of titanium alloys has continually stayed as an issue of pronounced attention among researchers. Titanium alloys remain very challenging to machine materials owing to their numerous innate possessions. The feed rate, rotational speed, drill tool diameter, tool geometry, etc., are the impelling parameters that impact drilled holes' quality [2]. To obtain a good outcome, it is better to understand the machining process and properties. Computer-driven software techniques like Response surface methodology and Taguchi techniques are engaged to optimize cutting process parameters in several snags. The Taguchi method helps in defining the unsurpassed amalgamation of factors under the chosen experimental conditions. Taguchi technique decreases the number of experiments necessary in outdated trials once the number of cutting process parameters surges. The Taguchi approach premeditates an orthogonal array that studies the complete parameter space with fewer experiment trials [3]. An additional statistical method, analysis of variance, is castoff to understand investigational data. ANOVA's main purpose is to determine the strongest influence that each design parameter presents [4].

Palani Kumar et al. [5] have conceded out experiments with HSS drill bit and castoff analysis of variance also regression aimed at scrutinizing both input and output physiognomies. Davim et al. [6] engaged Taguchi's method to elevate the process parameters for drilling CFRP composites. It is suggested that grey relational analysis can be used as an operative technique when more than one response characteristic is investigated.

Artificial intelligence methods have been accredited as an effective and alternate means for accurately modeling several engineering or other systems. The solitary method is fuzzy logic, which works on a mathematical model merging multi-valued logic and the concepts of probability to astounded intricate difficulties. Fuzzy logic offers additional intelligence and applied means to problem-solving with authoritative cognitive competencies confined by the smallest sum of rules [7-9].

Tosun [10] has successfully castoff the grey relational grade method for elevating the cutting parameters based on multiple responses. Kuo et al. [11] have demonstrated Taguchi's technique combined with grey relational grade exploration for augmenting the multi-objective problem. The fuzzy logic method forecasts the response physiognomies in a modest approach by employing fuzzy logic rule-centered prototypes. Fuzzy rules are established with a correlation among response as well as yield process variables. The fuzzy logic method is pragmatic to a wide array of presentations. A fuzzy logic rulebook can be effortlessly altered [12]. The fuzzy logic technique is founded on the degree of fact as an alternative to habitual Boolean reasoning [13]. Vimal et al. [14] industrialized a fuzzy logic model to envisage forces in cutting and torque. The investigation shows that the investigational outcomes and the anticipated values are justly closer to one another, which designated that the proposed model could be efficiently used to forecast forces in cutting and torque. Krishna Moorthy et al. [15] use the grey fuzzy approach to augment drilling parameters concerning multiple responses.

II. Equipment and Work Piece Materials Engaged In the Experimentation

Experimentations are conceded out on a high-speed three axes CNC machine rated up to 18000 rpm. A FLIR E60 thermal camera was used by installing it at a distance of 1.0 m from the drilling region to measure the temperature changes/rise throughout the experiment [16]. The major stages of the investigation are presented in Figure 2.

A. Experiment Design

Table 1 gives the designated levels of the drilling factors for the study. Recognizing the aims of the experimentation are the early arguments of DOE. The Taguchi technique involves decreasing the disparity in drilling over the strong DOE. Thus, 3-factor and 5-level design process parameters with Taguchi's L25 orthogonal array are used to design the experiments.

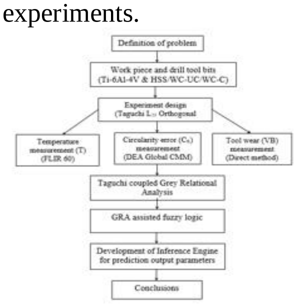

Figure 1 Proposed methodology

Figure 2 Investigational Test Set – Up

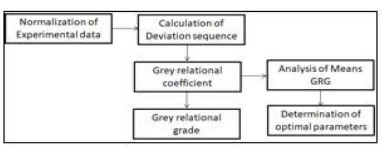

Figure 3 Procedure Adopted to Evaluate the Multiple Performance Characteristics

B.Optimization Through Grey Relational Analysis

In the present work, GRA, alongside the Taguchi method, is cast-off to optimize drilling process factors. Computing the resulting responses is the primary stage, i.e., values of S/N ratio smaller are either larger or better is superior type problem established on the variables output objective. The normalized novel order will achieve the mandatory impartial value. Then, novel order would be able to normalize by means of a direct method, i.e., permit the values of the original order to be divided by the preparatory value of the order [17]:

$$X_i^*(K) = \frac{X_i^0(K)}{X_i^0(1)} \quad (1)$$

Where Xi*(K) is the order after the data pre-processing and X_i^0 is the desired value of $X_i^0(K)$. where *i= 1,2,3…m*; *k = 1,2,3,...n.* Where *m* is the investigational data item number and *n* is the parameter number, and $Xi^0(K)$ indicates the original order. The normalized S/N ratio value of the reaction variables and their outcomes are given in Table 5. The procedure adopted to optimize the multiple performance characteristics is shown in Figure 3. Table 3 gives the calculated grey relational grade (GRG) and rank order corresponding to the cutting material used in the investigation. Table 4 gives the mean responses for circularity error (*Cr*), and Table 5 shows the mean responses for temperature (T). In contrast, Table 6 presents the mean responses for flank wear (VB) with diverse drill tool materials used as part of the investigation. Figure 4 presents the mean response graph for circularity error (Cr) versus rotational speed, N (in figure 4a), as well as feed rate, f (in figure 4b). Similarly, Figure 5 represents the mean response graph for temperature (T) versus rotational speed, N (in figure 5a), and versus feed rate, f (in figure 5b). Figure 6a presents the mean response graph for flank wear (VB) versus rotational speed (N), and Figure 6b presents the mean response graph for flank wear (VB) versus feed rate, f (in figure 6b).

Table 1. Table Factors of the Experiment Design and Respective Levels

Drilling factors	Level 1	Level 2	Level 3	Level 4	Level 5
Rotational speed, N, rpm	3500	5500	7500	9500	11500
Feed rate, f, mm/min	154	236	318	400	482
Depth of cut, d, 6 mm	constant	constant	constant	constant	constant
Drill material (Ø 12 mm)	HSS		Coated WC		Un-Coated WC
Work material	Ti-6Al-4V				
Output Responses	Circularity error, (C_r), µm		Temperature, (T), °C		Flank wear, (VB), mm

Later, the grey relational grade is resolute [18] by adopting the procedure shown in Figure 3. The mean reaction of grey relational grade for different drill bit materials is presented in Table 7. Figure 7a gives the mean reaction graph of grey relational grade for rotational speed (N), and Figure 7b shows the mean reaction graph of grey relational grade for feed rate (f).

C. Experimental Findings – as a base for Fuzzy Inference System

In this research, the multiple reactions are elevated for the input factors during drilling. The temperature, circularity error, and flank wear are deliberated as the response physiognomies in this work. The lowest value for flank wear, circularity error, and temperature factors are without a doubt for arriving finest quality of drilled holes. The impact of drilling factors such as feed rate, rotational speed as well as drill bit material type on drilling is significant, and it is analyzed.

Table 2 Experimental Findings

TC	N	F	HSS			Uncoated WC			Coated WC		
			C_r	T	VB	Cr (μm)	T (°C)	VB (mm	Cr (μm)	T (°C)	VB (mm
1	3500	15	0.056	150.99	0.28	0.045	120.76	0.23	0.034	107.51	0.13
2	3500	23	0.053	88.73	0.31	0.044	76.97	0.2	0.033	98.2	0.11
3	3500	31	0.051	78.84	0.31	0.044	66.45	0.17	0.023	83.37	0.09
4	3500	40	0.05	70.54	0.1	0.039	60.17	0.11	0.019	54.72	0.08
5	3500	48	0.047	49.97	0.08	0.035	36.92	0.09	0.021	43.93	0.02
6	5500	15	0.072	267.94	0.38	0.065	223.13	0.35	0.054	184.24	0.23
7	5500	23	0.065	197.45	0.28	0.064	206.78	0.35	0.051	115.87	0.22
8	5500	31	0.057	156.79	0.27	0.062	167.73	0.25	0.049	102.74	0.12
9	5500	40	0.057	111.34	0.21	0.059	156.38	0.18	0.046	94.58	0.12
10	5500	48	0.054	85	0.12	0.056	88.08	0.13	0.036	78.38	0.08
11	7500	15	0.053	360.19	0.46	0.071	291.3	0.46	0.049	246.84	0.31
12	7500	23	0.052	318.39	0.41	0.068	248.86	0.39	0.043	224.82	0.26
13	7500	31	0.05	190.67	0.29	0.055	213.07	0.32	0.039	216.94	0.26
14	7500	40	0.047	179.51	0.22	0.035	64.45	0.25	0.038	78.92	0.23
15	7500	48	0.047	124.59	0.18	0.032	42.5	0.18	0.029	59.62	0.18
16	9500	15	0.083	176.2	0.46	0.085	343.24	0.52	0.064	289.05	0.37
17	9500	23	0.081	483.56	0.55	0.069	228.21	0.47	0.059	226.1	0.36
18	9500	31	0.079	390.24	0.49	0.051	194.97	0.35	0.05	144.46	0.27
19	9500	40	0.078	382.47	0.4	0.034	152.66	0.35	0.043	102.26	0.24
20	9500	48	0.072	102.26	0.29	0.033	66.72	0.26	0.016	72.11	0.22
21	11500	15	0.058	562.46	0.61	0.062	464.69	0.53	0.042	365.68	0.45
22	11500	23	0.057	366.93	0.56	0.06	390.74	0.53	0.04	322.63	0.42
23	11500	31	0.055	363.43	0.52	0.059	381.33	0.44	0.03	290.46	0.32
24	11500	40	0.05	245.88	0.38	0.052	208.86	0.28	0.026	198.32	0.31
25	11500	48	0.045	51.54	0.34	0.043	168.87	0.27	0.024	63.66	0.26

Table 3 Calculated Grey Relational Grade (GRG) and Rank Order Corresponding to Cutting Material Used in the Investigation

Exp. No	High-speed steel, drill bit		Uncoated WC, drill bit		Coated WC, drill bit	
	Grey relational grade	Rank	Grey relational grade	Rank	Grey relational grade	Rank
1	0.6402	13	0.7133	11	0.7588	6
2	0.7026	8	0.7387	6	0.7234	3
3	0.7314	7	0.7839	4	**0.8646**	**1**
4	0.8824	3	0.8634	2	0.6946	5
5	**0.9683**	1	**0.9026**	**1**	0.8769	2
6	0.4741	22	0.5106	17	0.6502	8
7	0.5639	17	0.5461	14	0.6265	12
8	0.6337	14	0.7074	7	0.5459	13
9	0.6969	9	0.5875	12	0.5945	11
10	0.8091	4	0.5151	13	0.5552	14
11	0.5223	16	0.4179	25	0.7110	4
12	0.5548	15	0.6963	8	0.4297	25
13	0.6650	10	0.7916	3	0.4750	23
14	0.7411	6	0.7034	5	0.4846	21
15	0.8018	5	0.4587	20	0.6163	6
16	0.4714	21	0.6485	9	0.5347	17
17	0.3592	25	0.5386	19	0.5484	16
18	0.3936	24	0.5165	15	0.4849	19
19	0.4179	23	0.4678	22	0.6302	9
20	0.6005	12	0.6463	10	0.4298	24
21	0.4201	20	0.3873	23	0.4466	20
22	0.4719	19	0.5248	18	0.4964	17
23	0.4936	18	0.5445	16	0.4197	22
24	0.6091	11	0.5200	20	0.6186	10
25	0.8329	2	0.4009	24	0.5391	15

Table 4 Mean response for circularity error (C_r) with different drill bit materials

Level	High-speed steel		Uncoated WC		Coated WC	
	Rotational speed, N	Feed rate, f	Rotational speed, N	Feed rate, f	Rotational speed, N	Feed rate, f
1	0.05140	0.06440	0.04140	0.06560	0.02600	0.04860
2	0.06100	0.06160	0.06120	0.06100	0.04720	0.04520
3	0.04980	0.05840	0.05220	0.05420	0.03960	0.03820
4	0.07860	0.05640	0.05440	0.04380	0.04640	0.03440
5	0.08300	0.05300	0.05520	0.03980	0.03240	0.02520
Delta	0.02880	0.01140	0.01980	0.02580	0.02120	0.02340
Rank	1	2	2	1	2	1

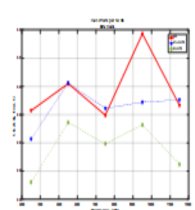

Figure 4a. Mean response graph for Circularity error (Cr) versus speed

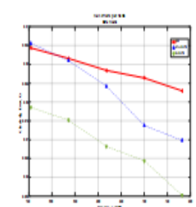

Figure 4b. Mean response graph for Circularity error (Cr) versus feed rate (f)

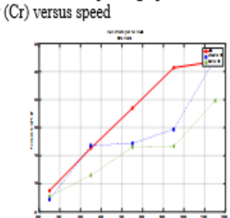

Figure 5a. Mean response graph for temperature (T) versus rotational speed (N)

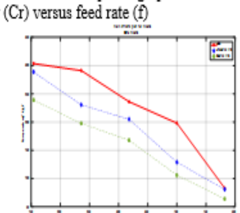

Figure 5b. Mean response graph for temperature (T) versus feed rate (f)

Table 5Mean responses for temperature (T).

Level	High-speed steel		Uncoated WC		Coated WC	
	Rotational speed, *N*	Feed rate, *f*	Rotational speed, *N*	Feed rate, *f*	Rotational speed, *N*	Feed rate, *f*
1	87.81	303.56	72.25	288.62	77.55	238.66
2	163.70	291.01	168.42	230.31	115.16	197.52
3	234.67	235.99	172.04	204.71	165.43	167.59
4	306.95	197.95	197.16	128.50	166.80	105.76
5	318.05	82.67	322.90	80.62	248.15	63.54
Delta	230.23	220.88	250.64	208.01	170.60	175.12
Rank	1	2	1	2	2	1

Table 6 Mean response for flank wear (VB) with the different drill bit

Level Flank wear	High-speed steel		Uncoated WC		Coated WC	
	Rotational speed, *N*	Feed rate, *f*	Rotational speed, *N*	Feed rate, *f*	Rotational speed, *N*	Feed rate, *f*
1	0.2160	0.4380	0.1600	0.4180	0.08600	0.29800
2	0.2520	0.4220	0.2520	0.3880	0.15400	0.27400
3	0.3120	0.3760	0.3200	0.3060	0.24800	0.21200
4	0.4380	0.2620	0.3900	0.2340	0.29200	0.19600
5	0.4820	0.2020	0.4100	0.1860	0.35200	0.15200
Delta	0.2660	0.2360	0.2500	0.2320	0.26600	0.14600
Rank	1	2	1	2	1	2

Table 7 Mean response of grey relational grade for different drill bit materials

Level	HSS		Uncoated WC		Coated WC	
	Rotational speed, N	Feed rate, f	Rotational speed, N	Feed rate, f	Rotational speed, N	Feed rate, f
1	**0.7850**	0.5056	**0.8004**	0.5355	**0.7837**	**0.6203**
2	0.6355	0.5305	0.5733	0.6089	0.5945	0.5649
3	0.6570	0.5835	0.6136	**0.6688**	0.5433	0.5580
4	0.4485	0.6695	0.5635	0.6284	0.5256	0.6045
5	0.5655	**0.8025**	0.4755	0.5847	0.5041	0.6035
Delta	0.3365	0.2969	0.3249	0.1333	0.2796	0.0622
Rank	1	2	1	2	1	2

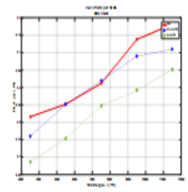

Figure 6a. Mean response graph for flank wear (VB)

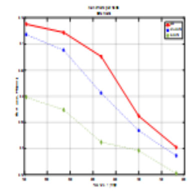

Figure 6b. Mean response graph for flank wear (VB) versus feed rate (f)

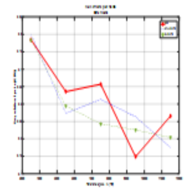

Figure 7a. Mean reaction graph for grey relational grade for rotational speed (N)

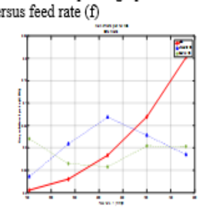

Figure 7b. Mean reaction graph for grey relational grade for feed rate (f)

In Table 3, trial no. 5 is specified in bold to illustrate the grey relational grade assessment's connotation, which is closer to '1' for HSS and uncoated WC. Furthermore, in Table 3, trial no. 3 is kept in bold for Coated WC to define the same. They are specified in bold to substantiate the connotation of grey relational grade assessments, which are higher to '1'. This highlights that the concomitant input factors are ideal for drilling the titanium composite employing HSS, Uncoated WC, and Coated WC tool materials independently.

III. Results and Discussions

Figure 4 – Figure 7 and Table 7 give a lucid interpretation of the best predominant factor impelling the response attributes. With HSS as tool material, for temperature, circularity error, and flank wear, the rotational speed is the principal actuating factor accompanied by the feed rate. Analogously, with uncoated tungsten carbide as the tool material, the feed rate is spotted to be the utmost impacting parameter parallel to spindle rotational speed. Simultaneously, for both the temperature and flank wear, the momentous parameter is interpreted as the spindle rotational speed. Moreover, with the coated carbide material drill tool, the feed rate is acknowledged as the noteworthy consideration in variance with spindle rotational speed for circularity error as well as temperature response factors. Simultaneously, for the flank wear, the rotational speed is consistently the dominating parameter. Therefore, the grey relational analysis is present to accomplish diverse yield features concurrent stretch for the supposed taking in factors. The effects of drilling parameters on spindle speed, feed rate, and drill material type on the multi-response outcomes in composite drilling are explored [19]. For exploring the findings, the average grey relational grades stay ascertained for elements portrayed in Table 7.

Figures 7(a) and 7 (b) entail the plots meant for the average grey relational grade utilizing HSS, uncoated WC, and coated WC as drill material types. In grey relational analysis, regardless of the performance patterns, the superior significance of the grey relational grade corresponds to adequate performance. Consequently, drilling factors are subjected, as the greater grey relational grade constitutes the primal prerequisite intended for machining titanium alloy. Accordingly, the ideal predicaments are the rotational speed at 3500 rpm with a feed rate of 482 mm/min, respectively, for accomplishing significantly low circularity error, temperature, and flank wear. Accordingly, the optimal settings are the rotational speed at 3500 rpm and with feed rate as 318 mm/min, correspondingly, for achieving favorable circularity error, temperature, and flank wear. Likewise, consequently, the finest conditions remain rotational speed as 3500 rpm and with feed rate as 154 mm/min, for obtaining favorable responses in flank wear, circularity error, and temperature.

Table 8 ANOVA for grey relational grade

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	2	0.4644	0.232199	28.21	0.000
Rotational speed, N	1	0.1959	0.195900	23.80	0.000
Feed rate, f	1	0.2685	0.268498	32.62	0.000
Error	22	0.1811	0.008230		
Total	24	0.6455			

Merely, an approximate ideal response is noticed in this work. For ascertaining the precise ideal response, the subsequent investigation is to be adopted. Grey relational grade plot and mean response table of GRG can review the impact of drilling parameters. The prominence of distinct machining parameters in compliance to multi-output features is to be examined; hence the ideal parameter thresholds of drilling could be recorded added deceptively. ANOVA (Table 8) is utilized for statistical examination of the solutions. It explores the machining parameters as well as displays the setting that prominently undermines the efficiency of drilling. It is accomplished through segregation of aggregate inconsistencies of grey relational grade, which in turn quantified by the sum of squared deviancies from the total mean of it into evaluations by individual drilling factor followed by an error [21]. ANOVA investigates the drilling factor and spots the setting that has a notable influence on the efficiency of drilling.

The regression model is formulated in commercial Minitab 18 software and also is reported in equations [(1), (2) & (3)] as,

$$GRG_{PRED}, HSS = 0.5689 - 0.000031.\ (N) + 0.000894.\ (f) \quad (1)$$

$$GRG_{PRED}, Uncoated\ WC = 0.8069 - 0.000033.\ (N) + 0.000144.\ (f) \quad (2)$$

$$GRG_{PRED}, Coated\ WC = 0.8234 - 0.000031.\ (N) + 0.000007.\ (f) \quad (3)$$

With the assistance of the regression model, GRG for each tool material is forecasted as well as matched with the estimated GRG values and are presented in Table 9. Based on this, it is concluded that the percentage of average error is rounded to 10.64 %, which is slightly on the upper flank. The regression model is adapted to 89.36 %.

IV. Development of Artificial Grey Fuzzy Inference System

Since the GRG_{PRED} results have excess flaws, a parallel methodology appealed to be AI methods. For example, fuzzy logic is implemented to formulate the model much more concisely. Methodology of fuzzy logic stands utilized to forecast the response features with an uncomplicated approach through devising a set of established fuzzy logic rule models [20].

Table 9 Comparison of (GRG_{CALC}) and (GRG_{PRED}) values

Exp. No.	GRG_{CALC}	GRG_{PRED}	Error %
1	0.6402	0.598076	6.58
2	0.7026	0.671384	4.44
3	0.7314	0.744692	1.78
4	0.8824	0.818000	7.30
5	0.9683	0.891308	7.95
6	0.4741	0.536076	11.56
7	0.5639	0.609384	7.46
8	0.6337	0.682692	7.18
9	0.6969	0.756000	7.82
10	0.8091	0.829308	2.44
11	0.5223	0.474076	9.23
12	0.5548	0.547384	1.34
13	0.665	0.620692	6.66
14	0.7411	0.694000	6.36
15	0.8018	0.767308	4.30
16	0.4714	0.412076	12.58
17	0.3592	0.485384	26.00
18	0.3936	0.558692	29.55
19	0.4179	0.632000	33.88
20	0.6005	0.705308	14.86
21	0.4201	0.350076	16.67
22	0.4719	0.423384	10.28
23	0.4936	0.496692	0.62
24	0.6091	0.570000	6.42
25	0.8329	0.643308	22.76
		Average Error (%)	10.64 %

An established set of fuzzy rules are compiled through a linkage among input as well as output variables. The phases obligated in drafting a fuzzy model are outlined hereunder:

- Establishment of membership function (even termed as fuzzification).
- Appropriate assortment of shapes and articulating the set of fuzzy logic rules.
- De-fuzzification.

The fuzzy inference system utilized is the 'Mamdani model' from the time when it was much adapted for human involvement. Fuzzy membership functions remain employed to articulate the fuzzy sets from the accessible variables. Variables in the entire framework stay fuzzified and remain introduced in clauses of fuzzy membership functions. In the present work, the fact-finding triangular membership function is employed [21-22]. The characteristic of this function is to reveal sustained escalation as well as declination properties. Due to this, only a unique value is customarily construed. Both input as well as output membership functions by way of their intervals are highlighted in Figures 8(a), 8(b), 8(c), and 8(d) and associated fuzzy terms displayed in Table 10.

A Fuzzy Logic System (FLS) has been instituted with the assistance of MATLAB 9.4 R 2018a software, Fuzzy Logic Toolbox. A set of fuzzy logic rules are fabricated and justified on the investigational conclusions, which confers the correlation among the input as well as output variables by way of dialectal declaration. A total of 125 sets of fuzzy rules were generated for the 25 investigational outcomes in the rule editor interface industrialized with MATLAB.

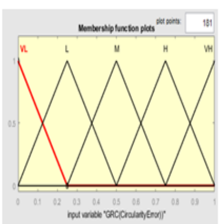

Figure 8(a) Membership function for GRC of Circularity error Cr

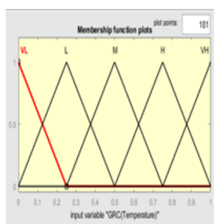

Figure 8(b) Membership function for GRC of Temperature, T

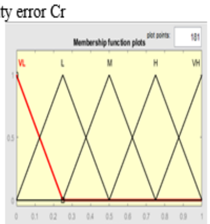

Figure 8(c) Membership function for GRC of Temperature, T

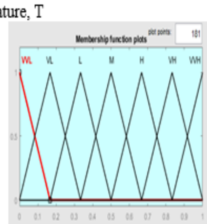

Figure 8(d) Membership function for Grey Fuzzy Reasoning Grade (GFRG)

Table 10 Fuzzy membership functions

Input Membership Functions			Output Membership Functions
Circularity Error	Temperature	Flank Wear	Grey Fuzzy Reasoning Grade
Very Low (VL)	Very Low (VL)	Very Low (VL)	Very Very Low (VVL)
Low (L)	Low (L)	Low (L)	Very Low (VL)
Medium (M)	Medium (M)	Medium (M)	Low (L)
High (H)	High (H)	High (H)	Medium (M)
Very High (VH)	Very High (VH)	Very High (VH)	High (H)
			Very High (VH)
			Very Very High (VVH)

The fuzzy philological rule encompasses a combination of the 'IF-Then' rule statement, and this is designed with the assistance of GRG of C_r, T, VB, and reaction outcome from GFRG. Conforming to the statement that higher-the-best GFRG is the superior reaction and 125 sets of fuzzy rules are leading for realizing the current FLS. For simulating the compiled fuzzy inference system structure, a total of 125 sets of fuzzy rules are engendered as well as set keen on the rule editor for the fuzzy logic toolbox, for instance, portrayed in Fig: 8.

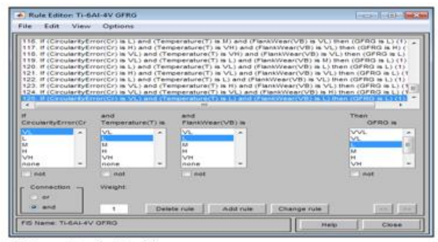

Figure 9 Rule Editor of Fuzzy Logic Tool box

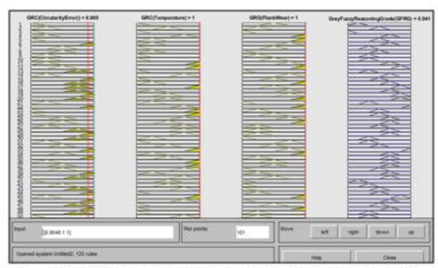

Figure 10 Output $GFRG_{HSS}$ of 0.941 for fuzzy logic reasoning at 0.905 (C_r), 1 (T) and 1 (VB)

Fig: 9 and Fig: 10 elaborate the graphic diagram for output fuzzy logic reasoning procedure that is estimated meant for inputs of GRC. The column in the rule viewer comprises the three variables C_r, T, VB as inputs and GFRG as lone multi-response variable. The rule viewer rows correspond to the introduced 125 fuzzy semantic rules predicted according to the criterion of greater GFRG. In every triangle, the dark zone height signifies the value of the membership function of that fuzzy set. An illustration for the de-fuzzified output value 0.632 is determined out of rule viewer corresponding to the 1st experiment, whereas de-fuzzified output value 0.941 represents the 5^{th} experiment.

The output values tabulated in table 11 remain de-fuzzified into a concise amount and are matched with evaluated GRG values. Consequently, the fuzzy set model is fit for 91.61 % with an error percentage of 8.38 %, correspondingly. The maximum GFRG value of 0.941 during the 5^{th} experiment is emphasized as the exemplary multi-response outcome amidst a total of 25 trials [23].

Table 11 Comparison of GRG as well as predicted GFRG values

Exp. No.	Grey Relational Grade (GRG)	Grey Fuzzy Reasoning Grade, (GFRG)	ERROR (%)
1	0.6402	0.6320	1.2740
2	0.7026	0.7470	5.9496
3	0.7314	0.7630	4.1461
4	0.8824	0.8060	8.6576
5	0.9683	**0.9410**	2.8148
6	0.4741	0.5370	11.7054
7	0.5639	0.5880	4.0945
8	0.6337	0.6240	1.5309
9	0.6969	0.7180	2.9448
10	0.8091	0.7730	4.4562
11	0.5223	0.6030	13.3823
12	0.5548	0.6230	10.9393
13	0.6650	0.7060	5.8024
14	0.7411	0.7660	3.2507
15	0.8018	0.7680	4.2099
16	0.4714	0.5610	15.9744
17	0.3592	0.4150	13.4573
18	0.3936	0.4420	10.9613
19	0.4179	0.4550	8.1600
20	0.6005	0.6500	7.6174
21	0.4201	0.5620	25.2422
22	0.4719	0.5740	17.7905
23	0.4936	0.5840	15.4769
24	0.6091	0.6750	9.7574
25	0.8329	0.8330	0.0131
		Average Error (%)	8.3844

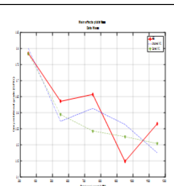

Figure 11a. Mean response graph for GFRG for rotational speed

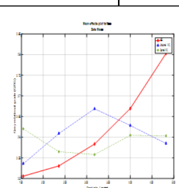

Figure 11b. Mean response graph for GFRG for feed rate

The optimal combination of the parameters is determined from the highest level of each response maintained at level 1 for spindle rotational speed and level 5 for feed rate, as shown in the main effect graph (Figure 11 (a) & (b)). Thus, the optimal parameter combination is N1-f5, for the HSS drill bit is the rotational speed at 3500 rpm and feed rate as 482 mm/min. The overall grey fuzzy reasoning grade is 0.941. The higher the mean of the grey fuzzy reasoning grade, the superior is the multiple performance characteristics [24].

Table 12 Mean reaction table for GFRG

LEVEL	Tool Material (HSS)		Tool Material (Un-Coated WC)		Tool Material (Coated WC)	
	Rotational Speed, N (rpm)	Feed rate, f (mm/min)	Rotational Speed, N (rpm)	Feed rate, f (mm/min)	Rotational Speed, N (rpm)	Feed rate, f (mm/min)
1	**0.7778**	0.579	**0.7832**	0.5748	**0.7716**	**0.6434**
2	0.648	0.5894	0.6254	0.641	0.6366	0.6068
3	0.6932	0.6238	0.664	**0.702**	0.5794	0.6038
4	0.5046	0.684	0.6098	0.6662	0.573	0.6356
5	0.6456	**0.793**	0.5372	0.6356	0.5674	0.6384
Delta	0.2732	0.214	0.246	0.1272	0.2042	0.0396
Rank	1	2	1	2	1	2

A. Analysis of Means (ANOM)

To finalize the ideal grouping of the process parameters, the ANOM of the GFRG is operated [25], as shown in Table 12. As per the design of experiments in the current investigation, the L25 orthogonal array is exercised. Therefore it is feasible to realize the emphasis of each parameter at diverse levels. Fundamentally, the greater mean value of grey fuzzy relational grade is the healthier multi-response. The response plot is charted and founded on the mean value of GFRG that is displayed in Figure 11 (a) & (b). Envisaging Table 12, the recommended drilling criterion are perceived to be curtailing the flank wear, circularity error, and temperature simultaneously remain rotational speed at 3500 rpm (1stlevel) and with feed rate as 482 mm/min (5thlevel) with HSS tool. Whereas rotational speed at 3500 rpm (1st level) and feed rate at the 318 mm/min (3rd level) for uncoated WC drill bit and for coated WC drill rotational speed at 3500 rpm (1st level) (3500 rpm) and feed rate as 154 mm/min (1st level).

B. Experimental validation

The validation testing is executed at the optimal factors to authorize the eminence features during drilling. The GFRG values as per the above exposition are $0.941_{(HSS)}$, $0.874_{(Un\text{-}Coated\ WC)}$, and $0.861_{(Coated\ WC)}$. This consequence is within the 95% confidence-level of the foreseen optimal circumstance as well as furthermore GFRG value of validation testing is enriched by 2% from the mean value. Consequently, the FIS built on the Taguchi technique for optimization of the multi-response problems is a highly favorable method for anticipating outcome responses. The reaction values by the validation chain on the optimal conditions are [26]:

Table 13 Optimum solutions for the responses

Tool Material	Cutting Parameters	Circularity error, C_r (mm)	Temperature, T (°C)	Flank wear, VB (μm)
HSS	Rotational speed at 3500 rpm (1st level) and feed rate as (482 mm/min) at 5th level	0.0449	107.49	0.064
Un-Coated WC	Rotational speed at 3500 rpm (1st level) and feed rate as (318 mm/min) at 3rd level	0.0452	96.32	0.1622
Coated WC	Rotational speed at 3500 rpm (1st level) and feed rate as (154 mm/min) at 1st level	0.0346	47	0.1378

V. Conclusions

Hole drilling operations have been performed with twist drill materials such as HSS, uncoated WC, and coated WC on Titanium alloy. Under inconsistent machining conditions, measured values of circularity errors, twist drill temperature, and drill tool wear were collected under different machining conditions. The succeeding suppositions were derived:

- The executed technique merges the GRA and Fuzzy Inference System (FIS) procedures, which approves in ascertaining the GFRG based on the GRC of each outcome. Grey fuzzy reasoning analysis (GFRA) clustered by means of Taguchi scheme for optimization of the multi-response problems is an extremely gratifying mechanism for anticipating the drill tool temperature, tool wear and circularity error in drilled holes.
- Miniature (circularity error values of 0.0449, 0.0452 and 0.0346), (flank wear's of 0.064 mm, 0.1622 mm and 0.1378 mm) and (temperatures of 107.49°C, 96.32°C and 47°C) at cutting parameters of (3500 rpm and 482 mm/min), (3500 rpm and 318 mm/min) and 3500 rpm and 154 mm/min) for HSS, un-coated WC, and coated WC, respectively. Here, the tool material serves a vital role in the disparity of the responses.
- Grey Relational Analysis and Mamdani model-based grey fuzzy inference systems are found to be effective in modeling and optimization of the drilling process.
- The average R^2 values of $0.941_{(HSS)}$, $0.874_{(Un\text{-}Coated\ WC),}$ and $0.861_{(Coated\ WC)}$ for all trained, validated, test, and overall experimental runs ascertained the model validity. A comparison of the R^2 values of the responses between grey fuzzy reasoning grade and grey relational grade acknowledged clear analogy.
- The optimal values (*Table 13*) are experimentally inspected for corroboration, from which it has been found that the forecasted values are obtained abutting the experimental values with tolerable deviations. The anticipated response values are contemplated to be within ± 2 % deviations from the substantial experimental outcomes.

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