Determination of optimum parameters for multi responses in drilling of Al 7075 - 10%SiC$_p$ Metal Matrix Composite under MQL condition using Taguchi-Fuzzy Approach

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Abstract - **Now a day the reasons for an increase in the interest to perform machining operations in dry/near-dry environments are health and safety on the cost, operator, ease of chip recyclability, etc. However the important machining process, which is difficult to perform in dry environment, is drilling. Without coolant, drilling leads to high thermal distortion and poor tool life. In order to overcome these conflicts, it is essential to study the machining performances with minimum quantity lubrication (MQL) environment and dry environment. In the present paper Drilling experiments are conducted according to Taguchi L$_{27}$ on AL7075-10%SiC$_p$ metal matrix composite with uncoated and coated HSS tools under MQL environment. The responses of drilling are analyzed using the Taguchi-Fuzzy model and the best combinations of process parameters are identified.**

Keywords - Metal Matrix Composite material, Drilling, Design of experiments, Taguchi-fuzzy logics, controllable parameters, optimal combination.

I. INTRODUCTION

Metal matrix composites (MMC) are widely used composite materials in aerospace, automotive, electronics and medical industries. They have outstanding properties like high strength, low weight, high modules, low ductility, high wear resistance, high thermal conductivity and low thermal expansion. These desired properties are mainly manipulated by the matrix, the reinforcement element and the interface (Kunz J. M et al., 2001). As the matrix element, aluminium, Titanium and magnesium alloy is used, while the popular reinforcements are silicon carbide (SiC) and alumina (Al2O3). Aluminium-based SiC particle reinforced MMC materials have become useful engineering materials due to their properties such as low weight, heat-resistant, wear-resistant and low cost (Hung N.P et al., 1996). However, the final conversion of these composites into engineering products is always associated with machining, either by turning or by milling. The recurring problem with MMCs is that they are difficult to machine, due to the hardness and abrasive nature of the reinforcing particles (Paulo Davim. J, 2002). The particles used in the MMCs are harder than most of the cutting tool materials. Most of the researchers reported that diamond is the most preferred tool material for machining MMCs (Lane. G 1992, Chadwick G.A 1989).

Taguchi method analyzes the influence of parameter variation on response characteristics. Thereby, an optimal result can be obtained from the sensitivity analysis respect to parameter variation (P.J. Ross 1998, R.K. Roy 2001). Several researchers have successfully applied this method for analyzing the drilling of metals, composites and metal matrix materials (S. Basavarajappa et al., 2008, Tsao. C.C 2009, Eyup Bagci et al., 2005). However, Taguchi method has shown some defects in dealing with the problems of multiple performance characteristics (B. Berginc et al., 2006, W. Grzesiket al., 2006). The grey system theory proposed by Deng (J. L. Deng, 1989) has been proven to be useful for dealing with poor, insufficient, and uncertain information. The grey relational theory is more useful for solving the complicated inter-relationships among multiple performance characteristics (H.S. Lu, 2006) like Multi response optimization of drilling parameters of Al/SiC metal matrix composite and Determination of optimum parameters for multi-performance characteristics in drilling (Erol Kilickap 2010, A. Noorul Haq et al., 2008). The theory of fuzzy logics, initiated by Zadeh, has proven to be useful for dealing the uncertain and vague information (L. Zadeh 1965). The definition of performance characteristics used for this research such as lower-the-better, higher-the-better, and nominal-the-better contains a certain degree of uncertainty and vagueness. Hence, fuzzy logics can be a proper basis to perform the optimization process (Y.J. Xing et al., 2006, F. Cus et al., 2007, N. H. Elmagrabi et al., 2007, W.F. Lin et al., 2006).

The cutting conditions which influence the machining process are coolant, tool type, speed, feed, depth of cut. Among those, coolant is an important factor largely affects the machining process (Kelly JF 2002, Nouari M et al., 2003). The modern industries are therefore looking for a cooling system to provide dry (near dry), clean, neat and pollution free machining . Minimum Quantity Lubrication (MQL) refers to the use of cutting fluids of only a minute amount-typically of a flow rate of 50-500 ml/hour which is about three to four orders of magnitude lower than the amount commonly used in flood cooling, for example, up to 10 liters of fluid can be dispensed per minute. The concept of MQL, sometimes referred to as 'near dry lubrication' or 'micro lubrication' Machining under minimum quantity lubrication (MQL) condition is perceived to yield favorable machining performance over dry or flood cooling condition (Kelly JF 2002, Nouari M et al., 2003). Tools with TiN, TiCN, CrN, and TiAlN coating also play an important role in drilling to improve multi performance (Erol Kilickap 2010, A. Noorul Haq et al., 2008, Nihat Tosun 2006, Lin TR et al., 2000).

In the present study, the Taguchi method with fuzzy logic is used as an efficient approach to determine the optimal machining parameters in drilling of Al7075-10%SiC_p metal matrix composite.

II. EXPERIMENTAL DETAILS

A. *Work material*

The work materials selected for the study is Al7075-10%SiCp metal matrix composite (rectangular plates of 25mm thickness 45 mm width and 60 mm long) which is prepared using stir casting unit (Fig. 1). It is highly used in aeronautical and automobile industries because of their high strength to weight ratio, mechanical and physical properties compared to monolithic material. Table I shows the physical and mechanical properties of Al7075-10%SiCp.

Fig. 1. Stir Casting Furnace

Fig. 2. Drill bits

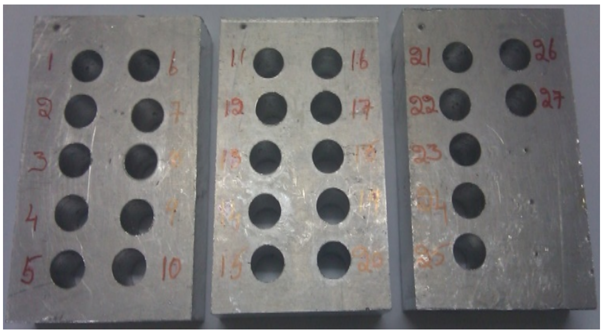

Fig. 3. Drilled Al7075-10%SiCp pieces

B. *Experimental design and drilling of work material*

Drilling tests have been performed on Al7075-10%SiCp(fig.3) work material using radial drilling machine with HSS, TIN and TiAlN coated HSS tools (Fig. 2) under Dry and MQL environment by considering different speed, feed, cutting fluid combination. The parameters such as power requirement, temperature, burr height, surface roughness are selected as indexes to evaluate cutting performance in drilling of Al7075-10%SiCp. Therefore these are considered as response characteristics in this study. Basically power, temperature, burr height and surface roughness should be low in drilling process for the better cutting performance (lower the better). In this experiment five controllable parameters are considered and each parameter is set at three levels. The machining parameters and their levels are shown in Table II. For full factorial design, the experimental runs required are (levels) $^{(factors)}$ equal to 3^5=243. To minimize the experimental cost, fractional factorial design is chosen, i.e., 3^{5-2}=27 runs. Therefore Taguchi experimental design L_{27} chosen for conducting experiments.

Experiments are performed according to this design and the values of power required (P), Temperature (T), burr height (BH) and surface roughness (SR) are recorded (Table III).

III. ANALYSIS OF EXPERIMENTAL RESULTS

The results obtained from the experiments are now analyzed to get optimal combination of process parameters by using Taguchi- fuzzy logic. Steps involved in this approach are follows.

A. Step-I: Calculation of S/N ratios

S/N ratios for the corresponding responses are calculated for different cases according to the required quality characteristics are as follows.

(i) Larger - the – better

$$\text{S/N Ratio}(\eta) = -10log_{10}\left(\frac{1}{n}\right)\sum_{1}^{n}\frac{1}{y_{ij}^{2}} \tag{1}$$

(ii) Smaller - the – better

$$S/N\ Ratio(\eta) = -10log_{10}\left(\frac{1}{n}\right)\sum_{1}^{n}y_{ij}^{2} \tag{2}$$

Where n= number of replications, y_{ij} = Observed response value where i=1, 2 ...n; j=1, 2...k. Larger the better is applied for problem where maximization of the quality characteristic is sought and smaller the better is applied where minimization of the quality characteristic is sought. For the present problem, smaller the better is applicable. Hence, its S/N ratios are calculated using Eq. (2) as shown in the Table IV.

TABLE I. Physical and mechanical properties of Al7075 – 10% SiCp

Material	**Tensile strength [Mpa]**	**Impact Strength [Mpa]**	**Hardness [BHN]**	**Density [gms/cm^3]**
Al7075 10%SiCp	58.34	632.9	229.5	3.1323

TABLE II. Machining Parameters and their levels

Parameter	**Level 1**	**Level 2**	**Level 3**
Speed (rpm) N	500	630	760
Feed (mm/Rev) F	0.2	0.3	0.36
Tool Material (TM)	TIN COATED HSS	TiAlN COATED HSS	HSS
Point Angle (Deg) PA	90	118	135
Cutting Environment (CE)	Dry (D)	Diesel (DIE)	Vegetable Oil (VG.OL)

B. Step II: Pre-processing of S/N ratios

Data pre-processing is required where the range and unit in one data sequence may differ from the others. In data pre-processing, the original sequence is transformed into a comparable sequence. Depending on the quality characteristic of a data sequence, there are various methodologies of data pre-processing are available.

TABLE III. Experimental Plan and Corresponding Results

Sl. No	Experimental plan					Corresponding Results			
	N	F	TM	PA	CE	P	T	BH	SR
1	1	1	1	1	1	1500	92	2.43	1.69
2	1	1	1	1	2	1600	75	1.17	3.27
3	1	1	1	1	3	1600	74	1.17	7.79
4	1	2	2	2	1	1500	58	1.35	6.56
5	1	2	2	2	2	1500	52	1.47	3.70
6	1	2	2	2	3	1600	60	1.28	2.6
7	1	3	3	3	1	1600	100	1.37	2.75
8	1	3	3	3	2	1500	69	1.31	2.60
9	1	3	3	3	3	1600	79	1.31	0.78
10	2	1	2	3	1	1500	101	1.32	1.61
11	2	1	2	3	2	1600	62	1.23	1.09
12	2	1	2	3	3	1600	97	1.31	0.95
13	2	2	3	1	1	1600	110	1.39	2.95
14	2	2	3	1	2	1700	80	1.26	6.08
15	2	2	3	1	3	1700	81	1.29	2.88
16	2	3	1	2	1	1600	98	1.11	3.41
17	2	3	1	2	2	1700	66	1.40	0.92
18	2	3	1	2	3	1700	91	1.35	5.79
19	3	1	3	2	1	1600	119	1.58	4.46
20	3	1	3	2	2	1600	88	1.54	6.13
21	3	1	3	2	3	1900	114	1.31	2.31
22	3	2	1	3	1	1900	94	1.86	5.68
23	3	2	1	3	2	1800	71	1.33	1.22
24	3	2	1	3	3	2000	101	1.33	4.66
25	3	3	2	1	1	2100	123	2.45	1.76
26	3	3	2	1	2	2300	87	1.29	0.26
27	3	3	2	1	3	2200	110	1.39	2.28

For quality characteristic of the "larger – the - better", the original sequence can be normalized as

$$x^*_i(k) = \frac{x^o{}_i(k) - \min x^o{}_i(k)}{\max x^o{}_i(k) - \min x^o{}_i(k)} \quad (3)$$

For the "smaller – the - better" is a characteristic of the original sequence, then the original sequence can be normalized as

$$x^*_i j(k) = \frac{\max x^o{}_i(k) - x^o{}_i(k)}{\max x^o{}_i(k) - \min x^o{}_i(k)} \quad (4)$$

Where $i = 1\ldots, m;$ $k = 1\ldots, n$. m is the number of experimental data items and n is the number of parameters. $x^o{}_i(k)$ Denotes the original sequence, $x^*{}_i(k)$ the sequence after the data pre-processing, max $x^o{}_i(k)$ the largest value of $x^o{}_i(k)$, min $x^o{}_i(k)$ the smallest value of $x^o{}_i(k)$, and x^o is the desired value. In this problem smaller the better is applicable and its S/N ratios are pre processed using Eq. (4) as shown in Table V.

C. Step III: calaculation of deviation sequences

After data pre processing , deviation sequences are to be calaculated by using the Eq. (5)

$$\Delta_i\,(\mathrm{k}) = \| 1 - x^*{}_i(k) \| \quad (5)$$

Where $i = 1\ldots, m;$ k= 1…, n. m is the number of experimental data items and n is the number of parameters, $x^*{}_i(k)$ is comparability sequence or the sequence after data pre processing. The deviation sequences are listed in the Table VI.

TABLE IV. S/N ratios

Sl. No	P	T	BH	S
1	-63.5218	-39.2758	-7.7121	-4.5577
2	-64.0824	-37.5012	-1.3637	-10.291
3	-64.0824	-37.3846	-1.3637	-17.8307
4	-63.5218	-35.2686	-2.6067	-16.3381
5	-63.5218	-34.3201	-3.3463	-11.364
6	-64.0824	-35.563	-2.1442	-8.2995
7	-64.0824	-40	-2.7344	-8.7867
8	-63.5218	-36.777	-2.3454	-8.2995
9	-64.0824	-37.9525	-2.3454	2.1581
10	-63.5218	-40.0864	-2.4115	-4.1365
11	-64.0824	-35.8478	-1.7981	-0.7485
12	-64.0824	-39.7354	-2.3454	0.4455
13	-64.0824	-40.8279	-2.8603	-9.3964
14	-64.609	-38.0618	-2.0074	-15.6781
15	-64.609	-38.1697	-2.2118	-9.1878
16	-64.0824	-39.8245	-0.9065	-10.6551
17	-64.609	-36.3909	-2.9226	0.7242
18	-64.609	-39.1808	-2.6067	-15.2536
19	-64.0824	-41.5109	-3.9731	-12.9867
20	-64.0824	-38.8897	-3.7504	-15.7492
21	-65.5751	-41.1381	-2.3454	-7.2722
22	-65.5751	-39.4626	-5.3903	-15.087
23	-65.1055	-37.0252	-2.477	-1.7272
24	-66.0206	-40.0864	-2.477	-13.3677
25	-66.4444	-41.7981	-7.7833	-4.9103
26	-67.2346	-38.7904	-2.2118	11.7005
27	-66.8485	-40.8279	-2.8603	-7.1587

TABLE V. Pre processed S/N ratios

Sl.	P	T	BH	SR
1	0	0.6627	0.9896	0.5505
2	0.151	0.4254	0.0665	0.7447
3	0.151	0.4098	0.0665	1
4	0	0.1268	0.2472	0.9495
5	0	0	0.3548	0.781
6	0.151	0.1662	0.18	0.6772
7	0.151	0.7595	0.2658	0.6937
8	0	0.3286	0.2092	0.6772
9	0.151	0.4858	0.2092	0.3231
10	0	0.7711	0.2189	0.5363
11	0.151	0.2043	0.1297	0.4216
12	0.151	0.7242	0.2092	0.3811
13	0.151	0.8703	0.2841	0.7144
14	0.2928	0.5004	0.1601	0.9271
15	0.2928	0.5148	0.1898	0.7073
16	0.151	0.7361	0	0.757
17	0.2928	0.2769	0.2932	0.3717
18	0.2928	0.65	0.2472	0.9127
19	0.151	0.9616	0.4459	0.836
20	0.151	0.6111	0.4136	0.9295
21	0.553	0.9117	0.2092	0.6425
22	0.553	0.6877	0.652	0.9071
23	0.4265	0.3617	0.2284	0.4547
24	0.673	0.7711	0.2284	0.8489
25	0.7872	1	1	0.5625
26	1	0.5978	0.1898	0
27	0.896	0.8703	0.2841	0.6386

D. Step IV: Determination of fuzzy reasoning grade

A fuzzy logic unit comprises a fuzzifier, membership functions, a fuzzy rule base, an inference engine and a defuzzifier.

TABLE VI. Deviation sequences

Sl. No	P	T	BH	SR
1	1	0.3373	0.0104	0.4495
2	0.849	0.5746	0.9335	0.2553
3	0.849	0.5902	0.9335	0
4	1	0.8732	0.7528	0.0505
5	1	1	0.6452	0.219
6	0.849	0.8338	0.82	0.3228
7	0.849	0.2405	0.7342	0.3063
8	1	0.6714	0.7908	0.3228
9	0.849	0.5142	0.7908	0.6769
10	1	0.2289	0.7811	0.4637
11	0.849	0.7957	0.8703	0.5784
12	0.849	0.2758	0.7908	0.6189
13	0.849	0.1297	0.7159	0.2856
14	0.7072	0.4996	0.8399	0.0729
15	0.7072	0.4852	0.8102	0.2927
16	0.849	0.2639	1	0.243
17	0.7072	0.7231	0.7068	0.6283
18	0.7072	0.35	0.7528	0.0873
19	0.849	0.0384	0.5541	0.164
20	0.849	0.3889	0.5864	0.0705
21	0.447	0.0883	0.7908	0.3575
22	0.447	0.3123	0.348	0.0929
23	0.5735	0.6383	0.7716	0.5453
24	0.327	0.2289	0.7716	0.1511
25	0.2128	0	0	0.4375
26	0	0.4022	0.8102	1
27	0.104	0.1297	0.7159	0.3614

In the fuzzy logic analysis, the fuzzifier uses membership functions to fuzzify the deviation sequences first. Next, the inference engine performs a fuzzy reasoning on fuzzy rules to generate a fuzzy value. Finally, the defuzzifier converts the fuzzy value into a fuzzy reasoning grade. The structure built for this study is a four input- one-output fuzzy logic unit as shown in Fig. 4. The function of the fuzzifier is to convert outside crisp sets of input data into proper linguistic fuzzy sets of information. The input variables of the fuzzy logic system in this study are the deviation sequences for Power, Temperature, Burr Height, and Surface Roughness. They are converted into linguistic fuzzy subsets using membership functions of a triangle form, as shown in Fig. 5, and are uniformly assigned into three fuzzy subsets-small (S), medium (M), and large (L) grade. The fuzzy rule base consists of a group of if-then control rules to express the inference relationship between input and output. A typical linguistic fuzzy rule called Mamdani is described as

Rule 1: if x1 is A1, x2 is B1, x3 is C1 andx4 is D1 then y is E1 else

Rule 2: if x1 is A2, x2 is B2, x3 is C2 andx4 is D2 then y is E2 else

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Rule n: if x1 is An, x2 is Bn, x3 is Cn andx4 is Dn then y is En else

In above Ai, Bi, Ci and Di are fuzzy subsets defined by the Corresponding membership functions i.e., α/4Ai, α /4Bi, α /4Ci, and α /4Di. The output variable is the Fuzzy grade yo, and also converted into linguistic fuzzy subsets using membership functions of a triangle form, as shown in Fig. 6. Unlike the input variables, the output variable is assigned into relatively nine subsets i.e., very very low (VVL), very low (VL), small(S) medium low (ML), medium (M), medium high (MH) high (H), very high (VH), very very high (VVH) grade. Then, considering the conformity of four performance characteristics for input variables, 81 fuzzy rules are defined and listed in Table VII. The fuzzy inference engine is the kernel of a fuzzy system. It can solve a problem by simulating the thinking and decision pattern of human being using approximate or fuzzy reasoning. In this paper, the max-min compositional operation of Mamdani is adopted to perform calculation of fuzzy reasoning. Suppose that x1, x2, x3 and x4 are the input variables of the fuzzy logic system, the membership function of the output of fuzzy reasoning grade can be expressed as

$$\mu_{C_0}(y) = \left(\mu_{A_1}(x_1)\Lambda\mu_{B_1}(x_2)\Lambda\ \ \mu_{C_1}(x_3)\Lambda\mu_{D_1}(x_4)\Lambda\ \ \mu_{E_1}(y)\right)\mathrm{v}$$
$$\ldots\left(\mu_{A_n}(x_1)\Lambda\mu_{B_n}(x_2)\Lambda\ \ \mu_{C_n}(x_3)\Lambda\mu_{D_n}(x_4)\Lambda\ \ \mu_{E_n}(y)\right)$$

Where V is the minimum operation and Λ is the maximum operation. Fuzzy Reasoning Grade is shown in the Table VIII.

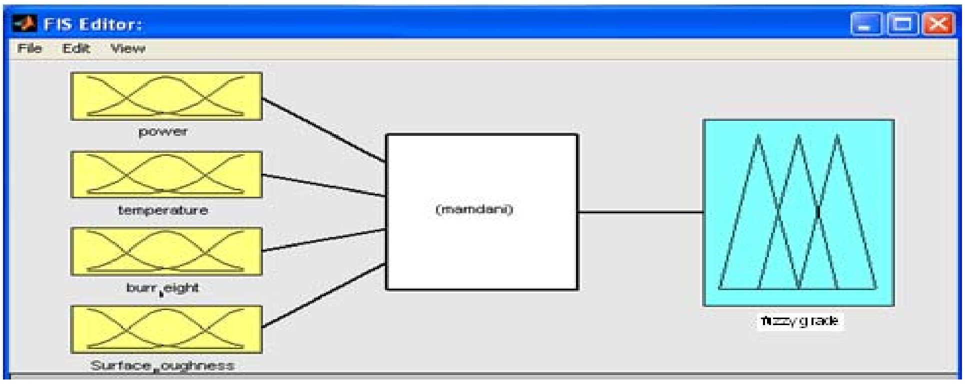

Fig. 4. Four input- one-output fuzzy logic unit

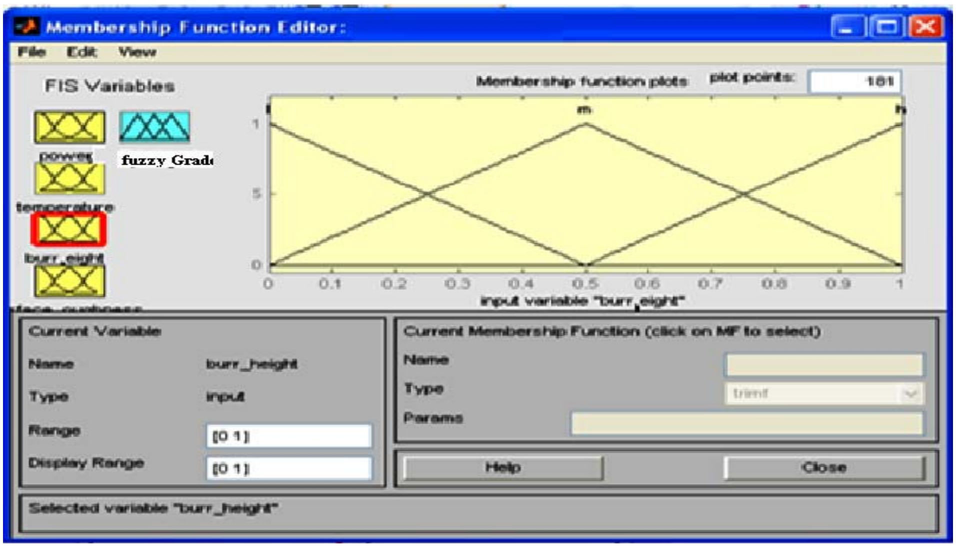

Fig. 5. Membership functions for Power, Temperature, Burr Height and Surface Roughness

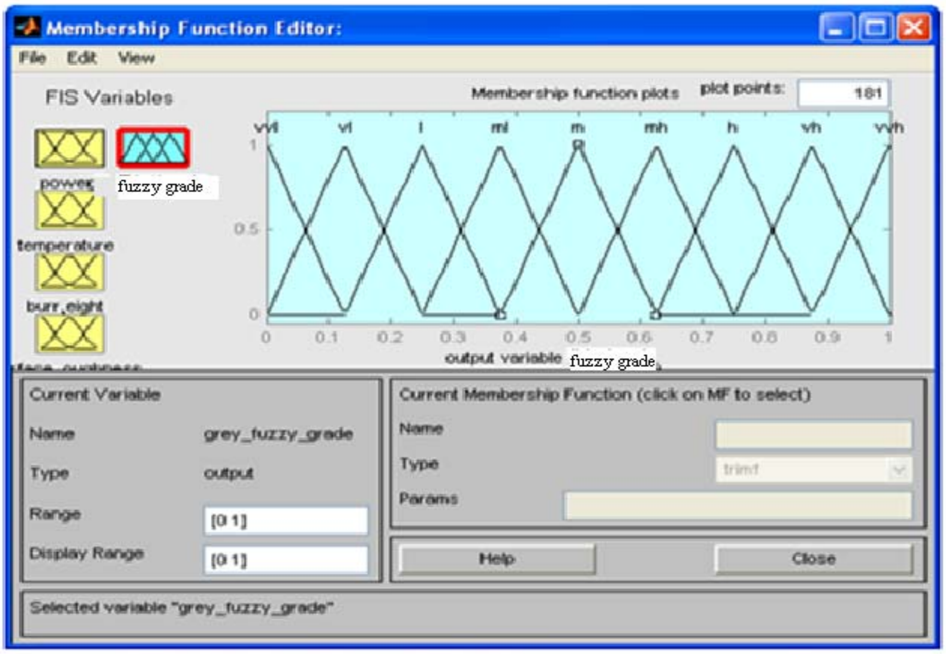

Fig. 6. Membership function for fuzzy Grade

TABLE VII. Fuzzy Rules

Rule no	**Deviation sequences as input variables**				**Output variables**
	P	**T**	**BH**	**SR**	**FG**
1	low	low	low	low	VVL
2	low	low	low	medium	VL
3	low	low	low	high	L
4	low	low	medium	low	VL
5	low	low	medium	medium	L
6	low	low	medium	high	ML
7	low	low	high	low	L
8	low	low	high	medium	ML
9	low	low	high	high	M
10	low	medium	low	low	VL
-	-	-	-	-	-
-	-	-	-	-	-
-	-	-	-	-	-
-	-	-	-	-	-
-	-	-	-	-	-
72	high	medium	high	high	VH
73	high	high	low	low	M
74	high	high	low	medium	MH
75	high	high	low	high	H
76	high	high	medium	low	MH
77	high	high	medium	medium	H
78	high	high	medium	high	VH
79	high	high	high	low	H
80	high	high	high	medium	VH
81	high	high	high	high	VVH

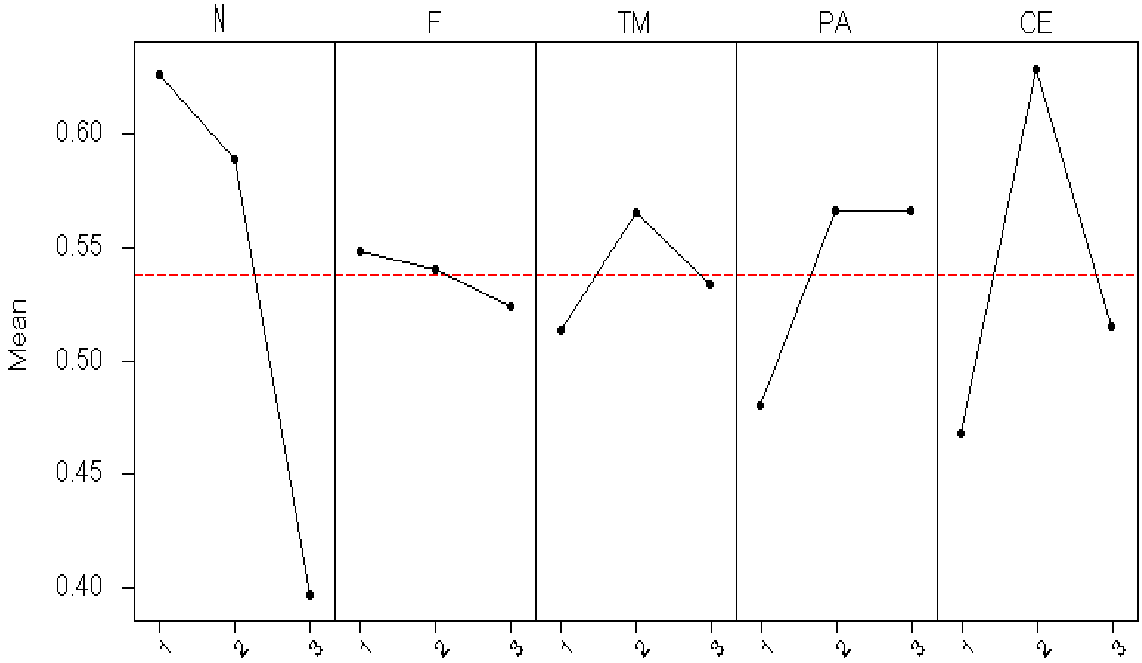

Fig. 7. Means of fuzzy grade

TABLE VIII. Fuzzy Grade

Sl. No	Fuzzy Grade	Sl. No	Fuzzy Grade
1	0.4391	15	0.5656
2	0.6433	16	0.5821
3	0.5861	17	0.6801
4	0.6661	18	0.4785
5	0.7262	19	0.4159
6	0.6656	20	0.4749
7	0.5234	21	0.4083
8	0.6913	22	0.3048
9	0.6988	23	0.6381
10	0.6138	24	0.37
11	0.7311	25	0.1782
12	0.6246	26	0.5406
13	0.4949	27	0.3441
14	0.5335		

TABLE IX. Fuzzy grade for each level of controllable parameter

Cutting Parameter	Level 1	Level 2	Level 3	max-min	Rank of effect on multi
Speed (N)	0.626656	0.589356	0.397211	0.229444	1
Feed (F)	0.548567	0.540533	0.524122	0.024444	5
Tool Material (TM)	0.513567	0.565589	0.534067	0.052022	4
Point Angle (PA)	0.48600	0.566411	0.566211	0.085811	3
Cutting Environment	0.468700	0.628789	0.515733	0.160089	2

TABLE X. Comparison between initial and optimal combination

Sl. No	Combination of Controllable	P	T	B H	S R
Initial Combinatio	N2, F2, TM2,PA2, CE2	2100	101	1.71 4	2.5 7
Optimal Combinatio	N1,F1, TM2, PA2, CE2	1600	61	0.75	1.2 4
Gain	N/A	500	40	0.59	1.3
% of Gain	N/A	23	40	50	51

IV. RESULTS FROM THE ANALYSIS

After obtaining the Fuzzy grade (Table VIII.), it is then to separate out the effect of each cutting parameter on the Fuzzy grade at different levels. The mean values of Fuzzy grade for each level of the controllable parameters and the effect of parameter on multi responses in rank wise are summarized in Table IX and in Fig. 7. Basically, large Fuzzy grade means it is close to the product quality. Thus, a higher value of the Fuzzy grade is desirable. From the Table VIII, the cutting parameters with the best level are spindle speed at level (*i.e.* 500 rpm), feed at level 1 (*i.e.* 0.2 mm/rev),, tool material at level 2 (*i.e.* TiAlN-HSS), point angle at level 2 (i.e.118^{O}) and Cutting environment at level 2 (*i.e.* Diesel). The optimal levels for the controllable parameters obtained from this methodology are verified. The experiments are conducted for initial and optimal conditions of controllable parameters and values are recorded. Table IX shows the comparison of the experiment results using the initial combination of the cutting parameters with the optimal one.

V. CONCLUSIONS

In this paper, the Taguchi-Fuzzy approach has been applied effectively for determining the optimum controllable parameters in drilling of Al7075-10%SiCp metal matrix composite. The results are that this approach provides a systematic and effective methodology for optimizing the cutting parameters. The confirmation test proved that the performance characteristics of the drilling process such as power, temperature, burr height, and surface roughness are minimized simultaneously through the use of optimal combination of the controllable parameters obtained from the Taguchi-Fuzzy method, which in turn reduces the manufacturing cost and greatly enhances manufacturing efficiency. This method can be also used for other processes while machining different materials.

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