Journal of Basic and Applied Engineering Research
Print ISSN: 2350-0077; Online ISSN: 2350-0255; Volume 2, Number 15; April-June, 2015 pp. 1292-1296

http://www.krishisanskriti.org/jbaer.html

Optimization of Machining Parameter of GFRP using Interval-valued Fuzzy TOPSIS

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Abstract—*Optimization of the machining parameters of Glass fiber reinforcement plastic is significant due to their wide application in various field such as automobile, biomechanics, aerospace industries and production of many electrical and marine components. The objective of this study is to optimize response by interval-valued fuzzy TOPSIS method, so as to obtain good surface finish, high material removal rate and low tool wear in turning of glass fiber reinforcement plastic. The experiment were conducted on lathe using carbide tool with three levels of input parameter such as cutting speed, depth of cut and feed rate. The result indicated that the optimization technique is greatly helpful in optimizing the multiple performance characteristics simultaneously in machining of glass fiber reinforcement plastic composite.*

1. INTRODUCTION

Glass fibre reinforced plastic (GFRP), an advanced composite material, is widely used in a variety of applications, including aircraft, robots, and machine tools [1]. Generally they are manufactured upto near net shape but in most cases machining is required like for making thread, groves, achieving the tolerance limit and required surface finish, which are difficult obtained during manufacturing of composite. Presence of non-homogeneous, anisotropic and abrasive constituents in GFRP results in excess tool wear, low accuracy, poor surface finish, matrix cracking, matrix burning, fibre delamination and fibre fragmentation [2] while machining. As a result numbers of attempts were made to improve machining performance of GFRP by tuning machining parameters like cutting speed, feed, and depth of cut [3]. Past studies basically concentrated on single machining performance and very few are devoted on optimization of multiple performance characteristics [4]. Most of the previous works ignore the vagueness, ambiguity and uncertainty in data arising because of variation of composition, constituent properties, machine condition and reliability of measuring instruments. The theory of fuzzy logics, initiated by Zadeh [5] has proven to be useful for dealing with uncertain and vague information. In this respect authors like Rajasekaran et al. [6] adopted fuzzy rule based system to multiple machining parameters and demonstrated the suitability of fuzzy inference system for optimization of composite machining. In fuzzy set theory, it is often difficult for an expert to exactly quantify opinion as a number in interval [0, 1]. Therefore, it is more suitable to represent this degree of certainty by an interval. Interval valued fuzzy sets were suggested for the first time by Gorzlczany [7] and Turksen [8]. The main reason for proposing this new concept is the fact that in the linguistic modelling of a phenomenon, the presentation of the linguistic expression in the form of ordinary fuzzy sets is not clear enough. In this regard present study adopted interval fuzzy set for optimization of machining parameters namely cutting speed (*N*), feed (*f*) and depth of cut (*doc*) of machining of GFRP during turning process. For this three performance measures namely surface roughness (R_a), tool wear rate (*TWR*) andmaterial removal rate (*MRR*) were considered. Study treated entire problem as multi criteria decision making (MCDM) and adopted full factorial design in combination with interval valued fuzzy TOPSIS (Technique for order preference by similarity to ideal solution) for selecting best alternative. The next section will give brief introduction to interval valued fuzzy number, followed by interval valued fuzzy TOPSIS in section 2.

2. INTERVAL VALUE FUZZY SETS

Imagine blurring the membership function depicted in Fig. 1(a) by shifting the points on the triangle not necessarily the same amounts as in Fig. 1(b). Then, for a specific value *x*, the membership function takes on different values, which are not all weighted the same. Doing this for all $x \in X$, a three dimensional membership function called type-2 membership function is formed which characterized interval value fuzzy set.

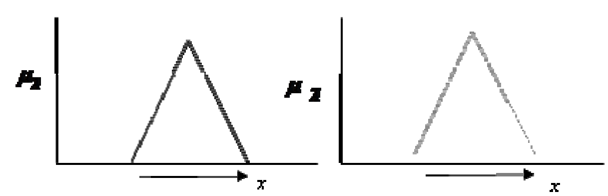

Fig. 1: (a). Triangular fuzzy number

(b) Type 2 triangular fuzzy number

Based on this an interval-valued fuzzy set ($\widetilde{A}$) defined on (-∞, +∞) is given by:

$$\widetilde{A} = \{(x, [\mu_{\widetilde{A}}^{L}(x), \mu_{\widetilde{A}}^{U}(x)]\}$$
$$\mu_{\widetilde{A}}^{L}, \mu_{\widetilde{A}}^{U} : X \to [0,1] \ \forall x \in X, \mu_{\widetilde{A}}^{L} \le \mu_{\widetilde{A}}^{U}$$
$$\mu_{\widetilde{A}}(x) = [\mu_{\widetilde{A}}^{L}(x), \mu_{\widetilde{A}}^{U}(x)]$$
$$\widetilde{A} = \{(x, \mu_{\widetilde{A}}(x))\}, x \in (-\infty, \infty) \quad \text{.... (1)}$$

$\mu_{\widetilde{A}}$ where $\mu_{\widetilde{A}}^{L}(x)$ the lower is limit of degree of membership and $\mu_{\widetilde{A}}^{U}(x)$ is the upper limit of degree of membership.

3. PROPOSED INTERVAL VALUE FUZZY TOPSIS METHOD

TOPSIS method is based on the idea that the best alternative should have the shortest distance from an ideal solution and maximum distance from negative ideal solution [9]. Ideal solution is composed of all the best attributes values achievable, while the negative ideal solution is composed of all worst attribute values achievable. Under interval value fuzzy environment attribute weights and performance rating of alternative for each attribute is expressed as linguistic variable defined in terms of type 2 triangular fuzzy number (T2TFN) [10].

Let $\widetilde{X} = [\widetilde{x}_{ij}]_{n\times m}$ be a fuzzy decision matrix for a multi criteria decision making problem having *n* alternatives and *m* attributes. So the performance of i^{th} alternative with respect to j^{th} attribute is denoted as $\widetilde{x}_{ij} = [(a_{ij}^{-}, a_{ij}^{+}), b_{ij}, (c_{ij}^{-}, c_{ij}^{+})]$.

Now the proposed approach to develop the TOPSIS for interval valued fuzzy data can be defined as follows:

Step1: Normalize the decision matrix.

The normalized performance rating ($\widetilde{r}_{ij}$) can be calculated as:

$$\text{if } j \in \Omega_b; \widetilde{r}_{ij} = [(r1_{ij}^{-}, r1_{ij}^{+}), r2_{ij}, (r3_{ij}^{-}, r3_{ij}^{+})] = \left[\left(\frac{a_{ij}^{-}}{c_j^{+}}, \frac{a_{ij}^{+}}{c_j^{+}}\right), \frac{b_{ij}}{c_j^{+}}, \left(\frac{c_{ij}^{-}}{c_j^{+}}, \frac{c_{ij}^{+}}{c_j^{+}}\right) \right]$$
$$\text{if } j \in \Omega_C; \widetilde{r}_{ij} = [(r1_{ij}^{-}, r1_{ij}^{+}), r2_{ij}, (r3_{ij}^{-}, r3_{ij}^{+})] = \left[\left(\frac{a_j^{-}}{a_{ij}^{+}}, \frac{a_j^{-}}{a_{ij}^{-}}\right), \frac{a_j^{-}}{b_{ij}}, \left(\frac{a_j^{-}}{c_{ij}^{+}}, \frac{a_j^{-}}{c_{ij}^{-}}\right) \right] \quad (2)$$
$$c_j^{+} = \max(c_{ij}^{+}) \quad \text{and} \quad a_j^{-} = \min(a_{ij}^{-})$$

where Ω_b and Ω_C are the set of the benefit attributes, and cost attributes respectively.

Step 2: Construct weighted normalize decision matrix.

Suppose that attribute relative importance in terms of other attributes expressed in terms of attribute weight is

$$\widetilde{w}_j = [(w1_j^{-}, w1_j^{+}), w2_j, (w3_j^{-}, w3_j^{+})]$$

Then weighted normalize decision matrix is calculated as:

$$\widetilde{V} = [\widetilde{v}_{ij}]_{n\times m}$$
$$\widetilde{v}_{ij} = \widetilde{r}_{ij} \times \widetilde{w}_j$$
$$\widetilde{v}_{ij} = [(g1_{ij}^{-}, g1_{ij}^{+}), g2_{ij}, (g3_{ij}^{-}, g3_{ij}^{+})] \quad (3)$$
$$\widetilde{v}_{ij} = [(r1_{ij}^{-} \times w1_j^{-}, r1_{ij}^{+} \times w1_j^{+}), r2_{ij} \times w2_j, (r3_{ij}^{-} \times w3_j^{-}, r3_{ij}^{+} \times w3_j^{+})]$$

Step 3: Determining the distance of the ith alternative from the ideal and negative ideal solutions.

The distance of the ith alternative from the ideal solution [(1, 1), 1, (1, 1)] is given as:

$$S_{i1}^{+} = \sqrt{[(g1_{ij}^{+} - 1)^2 + (g2_{ij} - 1)^2 + (g3_{ij}^{+} - 1)^2]}$$
$$S_{i2}^{+} = \sqrt{[(g1_{ij}^{-} - 1)^2 + (g2_{ij} - 1)^2 + (g3_{ij}^{-} - 1)^2]}$$

Similarly the distance of the ith alternative from the negative ideal solution [(0, 0), 0, (0, 0)] is given as:

$$S_{i1}^{-} = \sqrt{[(g1_{ij}^{+} - 0)^2 + (g2_{ij} - 0)^2 + (g3_{ij}^{+} - 0)^2]}$$
$$S_{i2}^{-} = \sqrt{[(g1_{ij}^{-} - 0)^2 + (g2_{ij} - 0)^2 + (g3_{ij}^{-} - 0)^2]}$$

Step 4: Calculate the relative closeness to the ideal alternatives:

The relative closeness is calculated as:

$$R_i = \frac{RS_{i2} + RS_{i1}}{2}$$

where

$$RS_{1i} = \frac{S_{i1}^{-}}{S_{i1}^{-} + S_{i1}^{+}}$$
$$RS_{2i} = \frac{S_{i2}^{-}}{S_{i2}^{-} + S_{i2}^{+}}$$

Step 5: Rank the alternatives:

Alternatives will be ranked according to the relative closeness to the ideal alternatives, the bigger is the Ri, the better is the alternative i.

4. EXPERIMENT PROCEDURE

The GFRP cylindrical shape specimen of length 150mm and diameter 50mm was used in this study. It is manufactured using filament winding process and consists of 60% by volume of E-glass and 40% by volume of epoxy. Turning operation on the specimen was performed on QETCOS-HMT LMT-20 Centre lathe using carbide K10 cutting tool. For machining three cutting parameters namely cutting speed (N), feed (f) and depth of cut (doc) at three different levels as shown in Table 1 were selected.

Table 1: Cutting parameters and their levels

Parameter	Symbol	Level			Unit
		1	2	3	
Cutting speed	N	150	250	420	rpm
Feed	f	2	3	4	mm/rev
Depth of cut	doc	0.10	0.20	0.30	mm

To accommodate all the possible combinations of three parameters each at three level total 27(3^3) experiments were performed as per full factorial experiment design.

The design matrix for the same is shown in Table 2.

Quality of turned part is measured in terms of average surface roughness (Ra), material removal rate (MRR)and tool wear rate (TWR). MRR and TWR were measured at each experimental run by subtracting the final weight (after machining) from the initial weight (before machining) of work piece and cutting tool respectively and then dividing it by machining time. Weight measurement is done by Mettler PM1200 which is having accuracy of measuring 3rd decimal place after gram. Time is measured using stopwatch having precession of 0.001s.

Table 2: Experiment design matrix

S.N.	N	f	doc	Ra (µm)	MRR(g/s)	TWR (g/s)
1	150	0.10	2	5.6694	3.823355	0.000658
2	150	0.10	3	3.8876	7.061111	0.001307
3	150	0.10	4	4.3304	8.721036	0.000324
4	150	0.15	2	4.3304	8.689103	0.000641
5	150	0.15	3	6.2666	11.50503	0.001258
6	150	0.15	4	4.5436	14.39005	0.001990
7	150	0.30	2	4.4076	16.04242	0.003030
8	150	0.30	3	8.1944	17.80441	0.003676
9	150	0.30	4	8.7468	21.85072	0.001449
10	250	0.10	2	5.4648	8.12000	0.001429
11	250	0.10	3	5.5120	13.73972	0.000709
12	250	0.10	4	9.7144	22.02552	0.003448
13	250	0.15	2	5.6666	14.33689	0.000971
14	250	0.15	3	5.9624	20.63274	0.000885
15	250	0.15	4	5.6568	21.26613	0.004032
16	250	0.30	2	8.6888	24.54103	0.005128
17	250	0.30	3	8.1266	41.13000	0.002500
18	250	0.30	4	7.3648	132.8381	0.009524
19	420	0.10	2	5.9246	11.10877	0.003509
20	420	0.10	3	5.9754	36.17119	0.005085
21	420	0.10	4	5.1008	27.83019	0.002830
22	420	0.15	2	4.7160	29.90000	0.005128
23	420	0.15	3	7.9948	56.85714	0.011429
24	420	0.15	4	5.4842	91.28200	0.006000
25	420	0.30	2	8.0710	135.6333	0.009524
26	420	0.30	3	10.4338	254.4095	0.004762
27	420	0.30	4	9.5578	235.0136	0.018182

5. OPTIMIZATION RESULTS

As shown in Table 2, for each alternative machining condition obtained by varying N, f and doc we have corresponding Ra, MRR and TWR attribute values. These values are classified into interval based fuzzy set by inference method. For each attributes five linguistic terms namely very low (vl), low (l), medium low (ml), medium (m), high (h) and very high (vh) were defined. The selection of criteria weight depends upon user requirement and can be given different values on the basis of relative importance of each attribute. In our study three attributes were considered and all were given equal weightage. These linguistic terms and attribute relative importance (w) for each attribute were defined using type 2 triangular fuzzy numbers and are given in Table 3.

Table 3: Linguistic variables & corresponding membership function

Surface roughness	
Very low (VL)	[(1.44,2.44);2.90;(3.36,4.36)]
Low (L)	[(2.90,3.90);4.36;(4.82,5.82)]
Medium low (ML)	[(4.36,5.36);5.82;(6.28,7.28)]
Medium (M)	[(5.82,6.82);7.28;(7.74,8.74)]
High (H)	[(7.28,8.28);8.74;(9.20,10.2)]
Very high (VH)	[(8.74,9.74);10.2;(10.66,11.66)]
Weight	[(0.75.0.85);0.95;(1, 1)]
Tool wear rate	
Very low (VL)	[(0.0003,0.0032);0.000325;(0.00164,0.00264)]
Low (L)	[(0.000325,0.001325);0.00264;(0.00398,0.00498)]
Medium low (ML)	[(0.00264,0.003640;0.00498;(0.00632,0.00732)]
Medium (M)	[(0.00498,0.00598);0.00732;(0.00866,0.00966)]
High (H)	[(0.00732,0.00832);0.00966;(0.011,0.012)]
Very high (VH)	[(0.00966,0.01066);0.012;(0.01334,0.01434)]
Weight	[(0.75.0.85);0.95;(1, 1)]
Material removal rate	
Very low (VL)	[(3.5,3.65);3.82;(18.2,23.2)]
Low (L)	[(3.82,8.82);23.2;(37.9,42.9)]
Medium low (ML)	[(23.2,28.2);42.9;(57.6,62.6)]
Medium (M)	[(42.9,47.9);62.6;(77.3,82.3)]
High (H)	[(62.6,67.6);82.3;(97,102)]
Very high (VH)	[(82.3,87.3);102;(116.7,121.7)]
Weight	[(0.75.0.85);0.95;(1, 1)]

The distance of the ith alternative from the ideal solution [(1,1);1;(1,1)] and negative ideal solution [(0,0);0;(0,0)]

shown in Table 4 and corresponding their relative closeness values is shown in Table 5.

Table 4: Distance from the ideal solution and negative ideal solution

S. No	Set of linguistic term			Distance from the ideal solution and negative-ideal solution	
	Ra	twr	mrr	$[S_{i1}^{+}, S_{i2}^{+}]$	$[S_{i2}^{-}, S_{i1}^{-}]$
1	M	VL	VL	[2.2792, 2.2403]	[0.9612, 0.9660]
2	VL	H	VL	[2.4074, 2.4379]	[0.6865, 0.5867]
3	L	VL	VL	[2.1497, 2.1160]	[1.0969, 1.0903]
4	M	ML	L	[2.5850, 2.5790]	[0.4727, 0.4545]
5	VL	H	L	[2.3101, 2.3260]	[0.8037, 0.7085]
6	L	ML	L	[2.4550, 2.4547]	[0.6084, 0.5789]
7	VH	ML	ML	[2.4982, 2.4846]	[0.5548, 0.5442]
8	H	M	ML	[2.4992, 2.4821]	[0.5515, 0.5461]
9	VH	M	ML	[2.5208, 2.5041]	[0.5298, 0.5241]
10	ML	L	VL	[2.4649, 2.5787]	[0.7460, 0.4548]
11	ML	VL	L	[2.1352, 2.0820]	[1.1265, 1.1341]
12	M	M	ML	[2.4685, 2.4513]	[0.5824, 0.5769]
13	M	L	L	[2.4148, 2.5133]	[0.8150, 0.5302]
14	M	L	ML	[2.2758, 2.3661]	[0.9496, 0.6727]
15	M	M	M	[2.3323, 2.3051]	[0.7238, 0.7248]
16	H	H	ML	[2.5092, 2.4917]	[0.5412, 0.5364]
17	H	ML	M	[2.3403, 2.3165]	[0.7179, 0.7140]
18	H	VH	H	[2.2495, 2.2093]	[0.8206, 0.8280]
19	VL	M	M	[2.0248, 2.0231]	[1.0901, 1.0085]
20	M	H	M	[2.3422, 2.3147]	[0.7135, 0.7151]
21	ML	ML	M	[2.2624, 2.2392]	[0.7970, 0.7913]
22	L	H	M	[2.2123, 2.1904]	[0.8492, 0.8394]
23	H	H	H	[2.2438, 2.2035]	[0.8264, 0.8387]
24	ML	H	H	[2.1654, 2.1263]	[0.9055, 0.9110]
25	VH	H	H	[2.2654, 2.2255]	[0.8048, 0.8117]
26	VH	VH	H	[2.2711, 2.2313]	0.7990, 0.8060]
27	VH	VH	VH	[2.1582, 2.1003]	[0.9438, 0.9562]

The last column of Table 5 shows the rank of each alternatives corresponds to their relative closeness value, greater the value of R_i, higher will be the rank. The highest rank alternative will be the most optimal solution. Experiment 11 have higher relative closeness value so it will be the best optimal solution. and the value corresponds to this experiment, *N=250 rpm, f=0.10 mm/rev and doc=3mm.*

Table 5: The interval of relative closeness& Rank

S. No	Interval of relative closeness		Ri	Rank
	RSi1	RSi2		
1	0.3013	0.2966	0.2989	5
2	0.1940	0.2219	0.2079	19
3	0.3401	0.3379	0.3390	3
4	0.1498	0.1546	0.1522	27
5	0.2335	0.2518	0.2458	14
6	0.1908	0.1986	0.1947	20
7	0.1792	0.1817	0.1807	23
8	0.1803	0.1808	0.1806	24
9	0.1731	0.1737	0.1734	26
10	0.1499	0.2323	0.1911	21
11	0.3526	0.3454	0.3490	1
12	0.1905	0.1909	0.1907	22
13	0.1742	0.2523	0.2133	18
14	0.2214	0.2944	0.2579	13
15	0.2392	0.2369	0.2380	15
16	0.1771	0.1774	0.1773	25
17	0.2356	0.2348	0.2352	16
18	0.2726	0.2673	0.2699	9
19	0.3327	0.3500	0.3413	2
20	0.2360	0.2335	0.2348	17
21	0.2611	0.2605	0.2608	12
22	0.2771	0.2774	0.2772	7
23	0.2745	0.2692	0.2718	8
24	0.2999	0.2948	0.2974	6
25	0.2673	0.2621	0.2647	10
26	0.2654	0.2602	0.2628	11
27	0.3128	0.3043	0.3086	4

6. CONCLUSION

An effective fuzzy multi-criteria analysis method incorporating the concepts of interval-valued fuzzy numbers is presented to solve multi objective machining composite problems which is treated as multi criteria decision making. In this paper, a linguistic decision process is proposed to solve multiple criteria decision making problem under fuzzy environment. According to this study, this paper finds that the proposed method can simultaneously obtain the gap between ideal alternative and each of the other alternative, the ranking order of alternatives to find the best alternative corresponds to their rank. Based on this experimental result conclusion are drawn, the optimal combination of process parameter for the MPCI are: cutting speed *N=250 rpm*, feed *f=0.10* mm/rev and depth of cut *doc=3mm.*

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