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A Fuzzy-ICA Based Hybrid Approach for Parametric Appraisal in Machining (Turning) of GFRP Composites

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Abstract: *Now-a-days, GFRP composites have gained immense attraction for their thermo-physical properties like light weight, high specific strength and stiffness etc. However, the machinability of these composites is a major issue for the manufacturers which hampers its popularity in usage. This paper aims to examine the influence of spindle speed, feed rate and depth of cut on the turning performances of GFRP composites. The turning performance characteristics have been evaluated in terms of material removal rate, surface roughness and cutting force. Here, (L16) orthogonal array based on Taguchi's robust design concept has been used for conduction of experiments. ANOVA has been also performed to examine the effects of machining variables on aforesaid performance characteristics. This paper also highlights a hybrid optimization approach for parametric appraisal in turning of GFRP composite using Fuzzy-ICA. Fuzzy Inference System (FIS) has been used to combine aforesaid multi-responses into single objective i.e. MPCI. A mathematical model is derived for MPCI through nonlinear regression analysis. ICA has been applied on this mathematical model to obtain the optimal machining condition.*

Keywords: FIS; GFRP, ICA

1. INTRODUCTION

As compared to convention materials, composite materials provide higher specific strength, stiffness and fatigue limit, low to weight ratio which enables them for structural design in many engineering applications. Due to aforementioned properties they have gained widespread application from household to industrial application mainly in aerospace and automotive sector. Hence, better understanding for machining of composites is essentially required to improve the accuracy and efficiency in machining operations. Since, turning is considered as primary operation in machining of GFRP composites; but the major problems faced during the machining of GFRP are fiber pull out, delamination etc. Hence, it is essential to select an appropriate machining condition to enhance the machinability aspects of these composites. Various researches have been carried out to investigate the influences of cutting variables for improving the surface quality and material removal rate.

Davim and Mata [1] adopted multiple regression analysis to optimize surface roughness and material removal rate in turning FRPs tubes manufacturing by filament winding and hand lay-up, using polycrystalline diamond cutting tools. Bagci and Isik [2] developed an empirical model to predict surface roughness by using artificial neural network (ANN) and response surface (RS) during the turning of GFRP with the help of cermet tools. Palanikumar and Davim [3] examined the effects of machining parameters, viz., cutting speed, feed rate, depth of cut and work piece fiber orientation angle in machining of GFRP composites. The study also developed a mathematical model to predict the tool wear using regression analysis. Verma et al. [4] applied fuzzy logic to study the effects of machining variables such as spindle speed, feed rate and depth of cut in order to improve MRR and surface finish during the turning of GFRP composites. Khan et al. [5] established a mathematical model in machining glass fibre reinforced plastic (GFRP) composite by using Ti[C,N] mixed alumina based ceramic cutting tool (CC650) and Si-C whisker reinforced alumina based ceramic cutting tool (CC670) for optimizing the unit production cost. The study utilized two different evolutionary algorithm based neural network namely, genetic algorithm based neural network (GA-NN) and particle swarm optimization based neural network (PSO-NN).

It has been revealed from literature that less extent of work has been done to obtain favorable machining condition by using evolutionary techniques. Most commonly genetic algorithm is used for optimization of process parameters in the field of machining. This paper highlights the application of fuzzy-ICA to evaluate the favorable process parameter combination during turning of GFRP composites.

2. EXPERIMENTAL DESIGN

In this present study, experimentation has been performed on the manually operated lathe [PINACHO]. For turning of GFRP, three governable process parameters: spindle speed, feed rate and depth of cut have been chosen and varied at four different levels as shown in (Table 1). Taguchi's philosophy has been applied to construct the experimental design as it reduces the number of experiments which saves experimental time and cost. A L_{16} orthogonal array has been chosen for the experimentation (Table 2). Here, only the main effects of machining parameters i.e. spindle speed, feed rate and depth of cut has been considered for assessing the optimal condition and their interaction effects has been considered as negligible. In this study, the performance of machining is evaluated in terms of material removal rate, surface roughness and cutting force. Material removal rate (MRR) can be explained as volume of material removed during machining w.r.t machining time.

$$MRR = \frac{(W_i - W_f)}{\rho . t_m} \frac{mm^3}{min} \tag{1}$$

W_i = Initial weight of the work piece, W_f = Final weight of the work piece, ρ = Density of the work material, t_m = Machining time

Here, Surface Roughness Tester SJ-210 (Make: Mitutoyo) has been used to measure the roughness average value based on carrier modulating principle. Cutting forces in all three directions (F_X, F_Y and F_Z) during machining of GFRP composites has been obtained using cutting tool dynamometer (Computerized Lathe Tool Dynamometer, Make: MEDILAB ENTERPRISES, Chandigarh, INDIA). The resultant cutting force (Fr) has been computed as below:

$$F_r = \sqrt{F_x^2 + F_y^2 + F_z^2} \tag{2}$$

Table 1: Domain of Experiments

Factors	Unit	Level 1	Level 2	Level 3	Level 4
Spindle Speed (N)	RPM	220	360	530	860
Feed rate (f)	mm/rev	0.06	0.066	0.72	0.077
Depth of cut (d)	mm	0.6	0.8	1	1.2

Table 2: DOE and Experimental Data

N [RPM]	F [mm/rev]	D [mm]	MRR [mm3/min]	Ra [μm]	Fr [kN]
220	0.060	0.6	1571.856	12.0613	38.5369
220	0.066	0.8	1497.006	15.9563	48.3727
220	0.072	1	2365.269	9.76066	68.3287
220	0.077	1.2	3368.263	17.1276	64.8527
360	0.060	0.8	1197.605	18.4423	26.7490
360	0.066	0.6	1137.725	20.2216	29.5188
360	0.072	1.2	2245.509	24.0876	46.4334
360	0.077	1	2035.928	11.7740	46.8114
530	0.060	1	1586.826	12.6080	48.4970
530	0.066	1.2	2994.012	21.2756	40.1330
530	0.072	0.6	2994.012	21.5373	24.7738
530	0.077	0.8	4491.018	21.4543	36.0519
860	0.060	1.2	5014.97	13.4570	45.9710
860	0.066	1	3532.934	11.0876	39.1064
860	0.072	0.8	4491.018	12.9996 7	40.7971
860	0.077	0.6	4358.458	15.3933	39.0403

3. METHODOLOGY

3.1 Fuzzy Inference System

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves the following elements: Fuzzification, Logical Operations, and If-THEN Rules and Defuzzification. Most commonly two types of fuzzy inference systems can be implemented: Mamdani type and Sugeno type. Mamdani's fuzzy inference method is the most commonly used fuzzy methodology. It was initially proposed in 1975 by Ebrahim Mamdani to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators [6-9].

Fuzzy inference systems have been applied in fields such as automatic control, data classification, decision analysis, expert systems, and computer vision [10]. Fig. 1 shows the basic structure FIS.

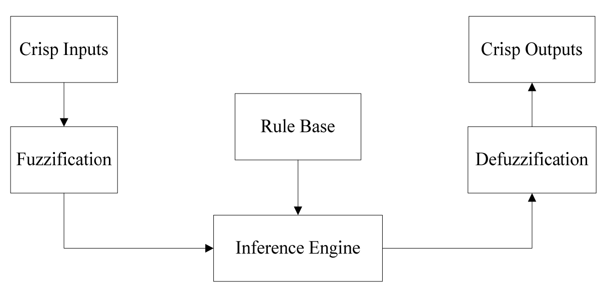

Fig. 1: Basic Structure of FIS

3.2 Imperialist Competitive Algorithm

Imperialist Competitive Algorithm (ICA) is a computational method inspired by the socio-political competition which gained more attention nowadays to solve optimization problems of different types in various fields [11-13]. Following are steps involved during the ICA:

1. Initialization of empire by selecting some random points on function.
2. Assimilation: the movement of colonies towards their relevant Imperialist.
3. If there is a Competitive in an empire which has lower cost than that of imperialist, exchange the positions of that Competitive and imperialist.
4. Compute the total cost of all empires (Related to the power of both imperialist and its colonies).
5. Pick the weakest Competitive (colonies) from the weakest empire and give it (them) to the empire that has the most likelihood to process it (Imperialistic competition).
6. Elimination of powerless empires as weak empires loses their power.
7. If there is only one empire, then stop, else go to step 2.

4. RESULTS AND DISCUSSIONS

4.1 Effect of Machining Parameters

This paper highlights the influence of machining variables such as spindle speed, feed rate and depth of cut on machining evaluation characteristics such as material removal rate, surface roughness and cutting force. The Taguchi method has been applied for analyzing the mean values of Signal-to-Noise (S/N) ratio in order to evaluate the significant parameters. Here, material removal rate (MRR) higher-is-Better (HB) criterion has been selected whereas for surface roughness and cutting force Lower-is-Better (LB) criterion has been selected for further analysis. ANOVA has been performed to investigate the main effects of process variables on these performance evaluation characteristics. The effect of main factors has been tested by using analysis of variance (ANOVA). From ANOVA (Table 3), it has been noticed that spindle speed is most significant factor for MRR whereas depth of cut has major influence on surface roughness and cutting force.

4.2 Optimization

In order to obtain the optimal machining condition, the fuzzy integrated with Imperialist Competitive Algorithm has been adopted. Fuzzy Inference system has been applied to convert the aforesaid characteristics into a single response i.e. MPCI. Finally, optimal solution is generated by using ICA on MPCI.

It is necessary to normalize the output responses (viz. MRR, surface roughness and cutting force) in a common scale i.e. 0 to 1 (0 is considered as worst value whereas 1 considered as best value) in order to eliminate the dimensional effect. Initially machining evaluation characteristics are normalized by using formulas given below:
For MRR (Higher-is-better):

$$\frac{X_{ij}}{X_{max}} \tag{3}$$

For surface roughness and cutting force (Lower-is better):

$$\frac{X_{min}}{X_{ij}} \tag{4}$$

The normalized value for each aforementioned characteristic (Table 4) is treated as input variable and the MPCI has been considered as output variable (Fig. 2). In calculating MPCI, three membership functions (Fig. 3-5) have been assigned to each of the input variables viz. (i) Normalized value of MRR (ii) Normalized value of Ra. (iii) Normalized value of Fr. The selected membership functions for individual input variables are: "small", "Medium", and "Large"; whereas for MPCI, five membership functions have been assigned: "Very Small", "Small", "Medium", "Large", and "Very Large" (Fig. 6). A set of 27 rules are formed which converts linguistic inputs into linguistic output (Fig. 7). Linguistic output is again converted to numeric values (MPCI) (Fig. 8) by de-fuzzification method (Table 4) by using centre of gravity method.

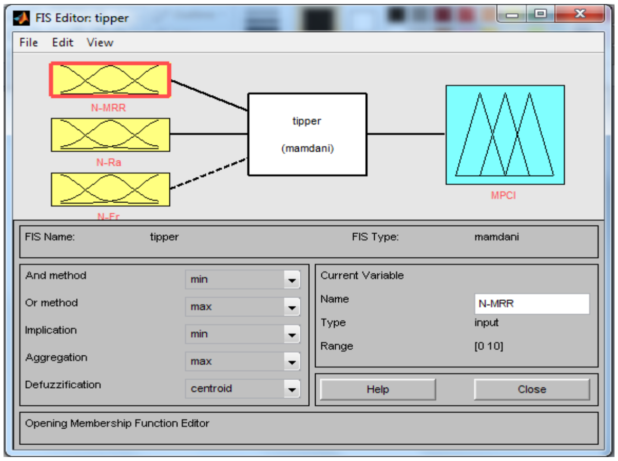

Fig. 2: FIS architecture to compute MPCI

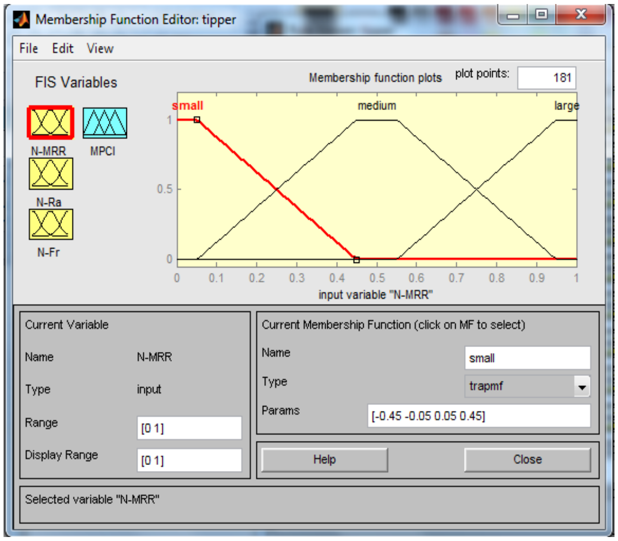

Fig. 3: Membership Functions (MFs) for N-MRR

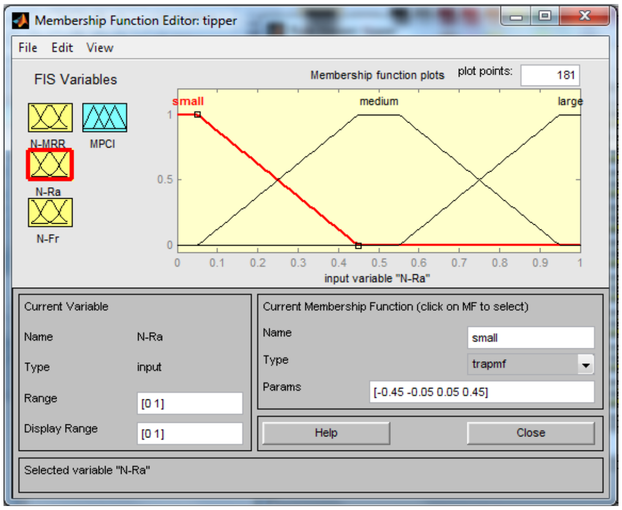

Fig. 4: Membership Functions (MFs) for N-Ra

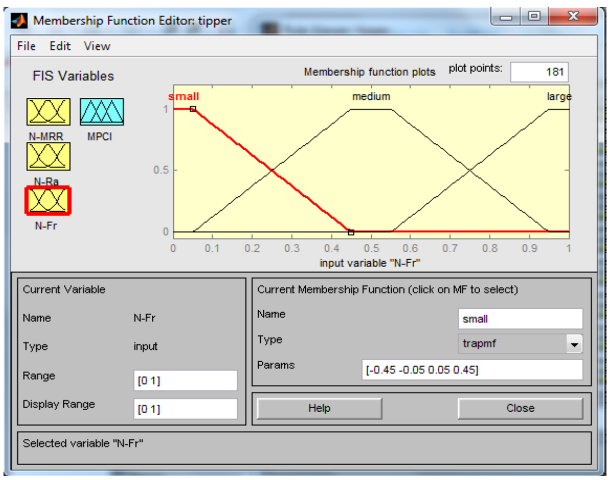

Fig. 5: Membership Functions (MFs) for N-Fr

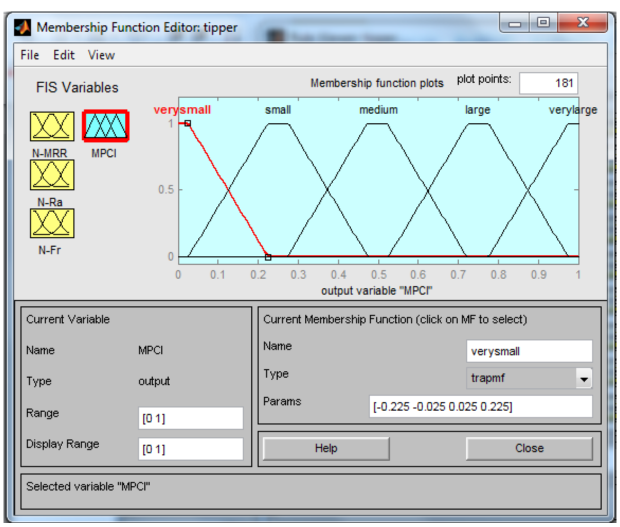

Fig. 6: Membership Functions (MFs) for MPCI

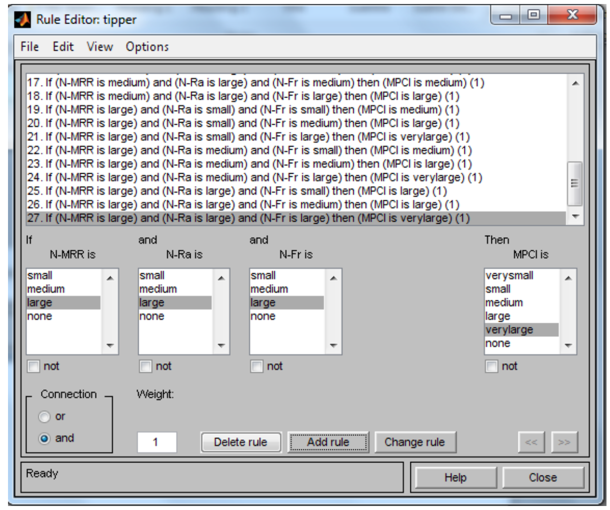

Fig. 7: Fuzzy RULE-BASE

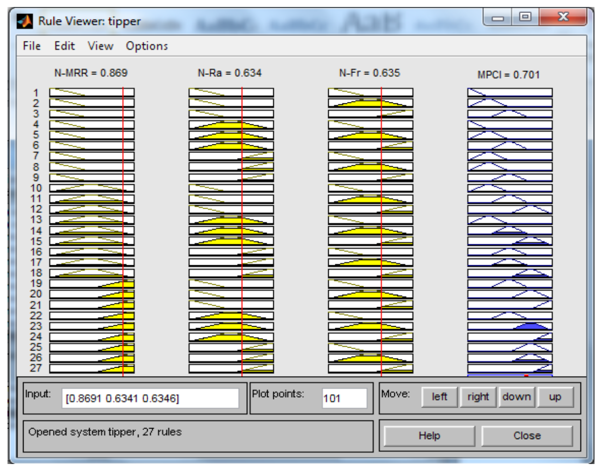

Fig. 8: Evaluation of MPCI with Fuzzy Rule Base

Nonlinear regression analysis is used to determine the relationship between the dependent variable and a set of independent variable. The proposed mathematical model for response is represented as below:

$$MPCI = C \times N^{x} \times f^{y} \times d^{z} \quad (5)$$

Here C denotes the constant; N denotes spindle speed; f denotes feed rate; d is the depth of cut and x, y and z are estimated coefficients of the said regression model. In the present work, Gauss-Newton algorithm has been used to generate the coefficients.

The mathematical model derived for MPCI is given as follows:

$$MPCI = 0.286 \times N^{0.283} \times f^{0.392} \times d^{(-0.155)}$$
$$(R^2 = 98.6\%) \quad (6)$$

The optimal setting for maximizing MPCI (in case of ICA) appears (N=860 RPM, f=0.0770 mm/rev, and d=0.6 mm). The fitness function value (predicted MPCI) for ICA appears as 0.7669 as shown in Fig. 9.

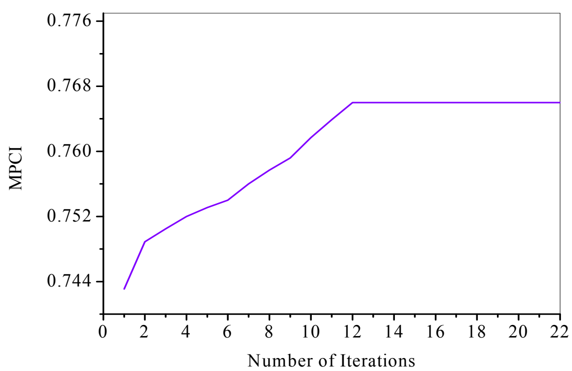

Fig. 9: Fitness function curve for MPCI

Table 4: Normalized Data

Sl. No.	N-MRR	N-RA	N-Fr	MPCI
1	0.313433	0.809253	0.64286	0.477
2	0.298507	0.611711	0.512144	0.399
3	0.471642	1	0.362568	0.497
4	0.671642	0.569877	0.382001	0.529
5	0.238806	0.529254	0.926159	0.596
6	0.226866	0.482684	0.839255	0.531
7	0.447761	0.405214	0.533534	0.495
8	0.40597	0.829002	0.529226	0.46
9	0.316418	0.774165	0.510832	0.402
10	0.597015	0.458772	0.617292	0.556
11	0.597015	0.453198	1	0.755
12	0.895522	0.454951	0.687171	0.724
13	1	0.725323	0.5389	0.75
14	0.704478	0.880317	0.633497	0.613
15	0.895522	0.75084	0.607244	0.703
16	0.86909	0.634084	0.63457	0.701

Table 5: Parameter settings for ICA

Parameters	Value assigned
Maximum decades	800
Number of Countries	80
Number of Imperialists	8
Number of Colonies	(No Countries - No Imperialists)
β	2
γ	0.1

5. CONCLUSIONS

In this paper, hybrid approach i.e. fuzzy inference system integrated with ICA has been implemented to obtain favorable machining condition during the turning of GFRP composites. ANOVA has also done to evaluate the effect of process parameters viz. spindle speed, feed rate and depth of cut on MRR, surface roughness and Cutting force. The fuzzy logic has been used to convert multi-responses into an equivalent single objective function (MPCI). The basic concept for ICA is competition among the imperialist for possession of colonies to increase their influence and empires. ICA has been adopted to obtain the best fitness value for MPCI. This algorithm provides reliable results with less computational efforts and time saving.

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