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Python implementation of fuzzy logic for artificial intelligence modelling and analysis of important parameters in drilling of hybrid fiber composite (HFC)

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Python implementation of fuzzy logic for artificial intelligence modelling and analysis of important parameters in drilling of hybrid fiber composite (HFC)

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Abstract. Composite materials present the advantage of being able to be specially designed for a particular application by combining appropriate reinforcement materials with a matrix material suited to withstand the operant conditions. The use of Hybrid-Fiber Composites (HFCs) addresses the need for greener manufacturing processes while also meeting product specifications in a wide range of applications, all for nominal prices. In order to improve our understanding of the machining processes compatible with HFCs, this paper presents findings from a study in which the effects of drilling on glass-flax-hemp fibre hybrid composite samples are observed and modeled. Pivotal parameters in drilling, namely drill bit diameter, spindle speed and feed rate are studied, and a fuzzy-logic inference system (FIS) coded in Python is used to model the thrust force and torque acting on the composite sample. A comparison between experimentally obtained and model-generated values of the same indicate very good correlation, thus verifying the effectiveness of the FIS.

1. Introduction

Composites have the ability to be custom-made according to the application necessity, are lightweight and easy to manufacture. This adaptable nature is achieved by changing the material matrix or reinforcement or the mixing ratio of reinforcement to matrix material [1]. This has diverse industrial applications in fields such as aerospace, civil engineering, electrical and electronics, automotive and many more. End-of-life action for conventional composite materials such as GFRP, CFRP etc. consist mainly of disposing the samples in landfills and dumps; this is problematic and potentially dangerous to local flora and fauna, owing to the non-biodegradable nature of such materials and their tendency to linger within the biomass present and contaminate it. The use of hybrid fiber composites containing naturally occurring reinforcement materials, such as flax, jute, hemp fibre, sisal etc. pose an elegant and easy-to-implement solution to this problem.

Ever-advancing research is being done in the area of hybrid fiber composites, both to understand their properties as well as to analyse their feasibility to replace conventional materials. HFCs containing cellulosic fibres are found to improve mechanical properties while driving down

costs [2]. Hybrid Fiber Composites have been identified as one of the best replacements for single-fiber reinforced composites. HFCs have been found to possess enhanced mechanical, thermal and damping properties when compared to single-fiber reinforced composites, thereby making them good replacements for wood, wood fiber composites and conventional materials [3].

Conventional machining processes like turning, facing, grinding, milling, drilling, welding, etc. are cornerstones in the field of component production and manufacturing. Machining of composite materials requires extreme care over critical process parameters such as material removal rate, machining forces acting on the billet, torque produced due to twisting motion in processes like drilling, milling etc. in order to avoid production of defects in the form of delamination of layers, internal and external cracks, surface burrs and irregularities among many others [4]. Consequently, the effects of various process parameters on composite materials are extensively studied and recorded.

Being an intensive process in terms of contact between tool and billet, and machining forces produced, drilling of fiber polymer composites HFCs has been widely studied for the ways in which it affects the integrity of the composite sample [5]. Of the methods used to join polymer composites, drilling is the most common method used, making it a vital process which needs extensive research on what process parameters must be used to machine the composites safely [6].

The work done by Davim et al. on drilling of GFRP indicates that feed rate is one of the significant parameters that dictates the thrust force generated [7, 8]. Nagarajan et al. analysed the drilling parameters of silk-glass hybrid composite and found that thrust force varies inversely with spindle speed, but directly with drill bit diameter [9]. Similar effects are observed in GFRP [11].

In this work, a composite sample with hemp fibre - flax - E-glass hybrid reinforcement is fabricated using the hand lay-up process and subjected to drilling. Three process parameters, namely spindle speed (rpm), feed rate (mm/min) and drill bit diameter (mm) are chosen for analysis. Different values for each parameter are decided and experiments are conducted with all possible combinations of the values. The thrust force and torque acting on the sample are experimentally recorded, taking the average of three trials.

Based on the observed data, a Fuzzy-Logic Inference System (FIS) is created, in which the observed input and output parameter ranges are defined and divided into "fuzzy" non-sharp sets. A set of qualitative "fuzzy" rules is created by experimentation and analysis of the experimental data, to map the correlation between different ranges of input and output parameters.

The newly developed system is fed the values of the set input process parameters, and the output values predicted by the model are recorded. A comparison is made between the experimentally obtained data and the predicted values, and the effectiveness of the model in predicting the thrust force and torque for a given set of inputs is quantified. The excellent correlation observed between the two sets suggests that the model is a very good fit to the data and that an accurate capture of the process parameters is possible.

2. Experimentation
The raw materials used in the fabrication of the hybrid fiber composite were:

(i)   Epoxy Resin (Araldehyde LY 556)

(ii) Hardener (Araldite) - HY 951

(iii) Fiber layers (Glass fiber- 2, Flax fiber- 3, hemp fiber- 2)

(iv) Gel coat- liquidity epoxy resin

(v)   Releasing agent

Hand layup process was used to fabricate the composite due to minimum investment in the mould. The individual thicknesses of the reinforcement mats were 0.2 mm (e-glass fiber), 0.35 mm (flax fiber) and 0.6 mm (hemp fiber). The final sample was 12 mm thick, and the fibers were stacked in the order as shown in figure 1. Taking the example of work done by Palanikumar et al. [8], Nagarajan et al. [9] and Samsingh et al. [13], and also owing to financial constraints, the volume fraction of the resultant composite was neither determined nor considered for analysis.

A hand roller was used to impregnate the reinforcement layer. The roller is used each time to obtain the desired thickness and prevent the formation of bubbles. After the layering process, the sample was cured at room temperature for 24 hours. After all these processes, drilling operations were performed on the fabricated workpiece, using the drilling machine as in figure 2.

| Flax |
| Hemp |
| Glass |
| Flax |
| Glass |
| Hemp |
| Flax |

Figure 1: Fiber stacking sequence used in the composite sample

Figure 2: Hand-layup process & Experimental set-up

3 operant parameters, namely spindle speed (rpm), drill bit diameter (mm) and feed rate (mm/min) were chosen and 3 possible values were chosen for each, leading to a total of 27 unique combinations of process parameters. The operant parameters were chosen based on the results obtained by Vantaki et al. [4], Davim et al. [7] and Palanikumar et al. [8]. Considering the choice of 3 control parameters each with 3 levels of values, a Taguchi L_{27} Orthogonal array was chosen for parameter specification, analysis and experiment design. This is an orthogonal array capable of considering 13 variables at three levels and three interactions. The degrees of freedom of the experiment is $27 - 1 = 26$. The degrees of freedom of the scenario considered for the three parameters at three levels is $3 \times (3 - 1) = 6$. The chosen values and assigned levels are specified in table 1, and the L_{27} array is shown in table 2.

Table 1: Selected control parameters for experimentation

S.No	Parameter	Levels		
		1	2	3
1	Spindle Speed (rpm)	500	1000	1500
2	Feed Rate (mm / min)	60	120	180
3	Drill Bit Diameter (mm)	4	6	8

A Kistler Quartz 3-Component piezo-electric dynamometer of type 9257B was used for measurement of thrust force and torque acting on the sample. The drill bit used in each case was an 8-facet solid carbide drill bit with 4 faces having 2 cutting edges each, having 2 point angles of $90°$ and $180°$. The drilling procedure was carried out using a CNC vertical machining center, details of which are given in table 3.

For each combination of the control parameters, the experimental procedure was conducted three times, and the value of the thrust force and torque measured in each trial was recorded on local storage. The average of the three trials for each experiment was computed and considered for analysis. Considering the results of the work done by Fernández-Pérez et al. [10], lubrication was not provided in order to aid in the thermal softening and easy drilling of the HFC sample.

Table 2: Taguchi L27 orthogonal array for Design of Experiments

Expt.	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	3	3
5	1	2	2	2	2	2	2	3	3	3	1	1	1
6	1	2	2	2	3	3	3	1	1	1	2	2	2
7	1	3	3	3	1	1	1	3	3	3	2	2	2
8	1	3	3	3	2	2	2	1	1	1	3	3	3
9	1	3	3	3	3	3	3	2	2	2	1	1	1
10	2	1	2	3	1	2	3	1	2	3	1	2	3
11	2	1	2	3	2	3	1	2	3	1	2	3	1
12	2	1	2	3	3	1	2	3	1	2	3	1	2
13	2	2	3	1	1	2	3	2	3	1	3	1	2
14	2	2	3	1	2	3	1	3	1	2	1	2	3
15	2	2	3	1	3	1	2	1	2	3	2	3	1
16	2	3	1	2	1	2	3	3	1	2	2	3	1
17	2	3	1	2	2	3	1	1	2	3	3	1	2
18	2	3	1	2	3	1	2	2	3	1	1	2	3
19	3	1	3	2	1	3	2	1	3	3	1	3	2
20	3	1	3	2	2	1	3	2	1	1	2	1	3
21	3	1	3	2	3	2	1	3	2	2	3	2	1
22	3	2	1	3	1	3	2	2	1	1	3	1	1
23	3	2	1	3	2	1	3	3	2	2	1	2	2
24	3	2	1	3	3	2	1	1	3	3	2	3	3
25	3	3	2	1	1	3	2	3	2	2	2	2	3
26	3	3	2	1	2	1	3	1	3	3	3	3	1
27	3	3	2	1	3	2	1	2	1	1	1	1	2

Table 3: Details of machining center

CNC Vertical Machining Center	
Manufacturer / Model	Bharat Freitz Werner, Bangalore / BMV 40 T20
CNC Control System	SIEMENS 802D
Table size	710 mm × 400 mm
Traverse (x, y, z)	510 mm × 410 mm × 460 mm
Magazine capacity	20 tools
Spindle speed range	60 – 6000 rpm
Spindle motor	AC 10 kW
Total connected load	25 kVA

Figure 3: 8-facet solid carbide drill bit

3. Construction of Predictive Computer Model in Python using Fuzzy Logic

Usage of fuzzy logic modelling to predict process parameters has been widely studied, with algorithms largely being implemented in MATLAB, using the Fuzzy Logic toolbox [12, 13]. In this work, a novel approach to the same has been taken, where Python code was developed open-source, which made use of the scikit-fuzzy (skfuzzy) module in tandem with other popular Python data-analysis packages such as numpy, pandas and matplotlib.

Unlike regular classification models which unilaterally determine the category to which the result of a set of inputs belongs, fuzzy modelling does not make sharp distinctions between classes. Instead, fuzzy logic works based on a set of rules, which map a certain range of input parameters to one or more such ranges in the output space, which is then disambiguated by evaluating the "membership" (0 being a non-member, 1 being a definite member) of the obtained output value. A general statement of the rules may be as shown below:

Rule 1: If x_1 is A_1, x_2 is B_1. . . x_n is Z_1, then y_1 is K_1
Rule 2: If x_1 is A_2, x_2 is B_2. . . x_n is Z_2, then y_2 is K_2
. . .
Rule n: If x_1 is A_n, x_2 is B_n. . . x_n is Z_n, then y_n is K_n

Here, $x_1, x_2 \ldots x_n$ are the inputs given to the model and $y_1, y_2 \ldots y_n$ are the outputs corresponding to each of the n cases, $A_1, A_2 \ldots A_n$, $B_1, B_2 \ldots B_n$ and $Z_1, Z_2 \ldots Z_n$ are the fuzzy membership functions for the inputs, and $K_1, K_2 \ldots K_n$ are the fuzzy membership functions for the outputs.

In the MATLAB Fuzzy Logic Toolbox, the inputs and outputs are defined using a visual GUI, while code snippets with appropriate ranges for each fuzzy set are written for defining each membership function of the input and output parameters when using the Python skfuzzy module.

The skfuzzy module is an open-source Python module with a framework to define input and output parameters and "fuzzify" them, and establish a set of rules to map a given combination of inputs to a fuzzy membership function in the output. It allows the definition of the required input parameters by taking the range of variation of values, and subdividing them into fuzzy membership functions which overlap with each other over the range of inputs. As a result, each input value does not have a definite category, but rather has varying degrees of membership (from 0 to 1, being a non-member to being a member of only that category) in multiple categories. The same goes for possible output values.

The program written to perform the fuzzy-logic modelling follows this algorithm:

(i) Define the Antecedents (input parameters) by specifying their labels (eg. 'Spindle Speed') and their ranges of variation (eg. 500 to 1500 rpm).

(ii) Create 3 triangular membership functions for each Antecedent and assign qualitative labels to each function / category such as 'Low', 'Medium', and 'High'.

(iii) Define the Consequents (output parameters) by specifying their labels (eg. 'Torque') and their ranges of variation observed experimentally.

(iv) Create 9 triangular membership functions (for improved accuracy) for each Consequent and assign qualitative labels to each function / category as needed.

(v) Define the rules of operation as a Rule set which maps each combination of Antecedent categories to a Consequent category (In this work, rules were defined by considering the experimentally observed data and using trial and error to determine the rule set which gave the best fit mapping).

(vi) Assign Antecedents, Consequents and Rule set to a Fuzzy logic Inference System (FIS) which can take input values, map them to the Antecedents, find the suitable Consequent categories and 'defuzzify' the Consequent values using the degree of membership of the Antecedents and Consequents.

(vii) Perform this mapping for all input parameters given in table 1 to get predicted output values.

(viii) Plot relevant images using separate data visualization modules.

In the model, the ranges of variation of the control parameters (drill bit diameter, spindle speed, feed rate) were fed into the code and split into 3 membership functions each, with qualitative labels namely 'Low', 'Medium' and 'High'.

In order to improve accuracy and correlation between observed and predicted values, the range of experimentally obtained output values was imported and split into 9 fuzzy membership functions with qualitative labels namely 'Ultra Low', 'Very Low', 'Low', 'Low-Medium', 'Medium', 'High-Medium', 'High', 'Very High' and 'Ultra High' categories.

The fuzzy sets for the control parameters and output parameters are respectively shown in figures 4 and 5.
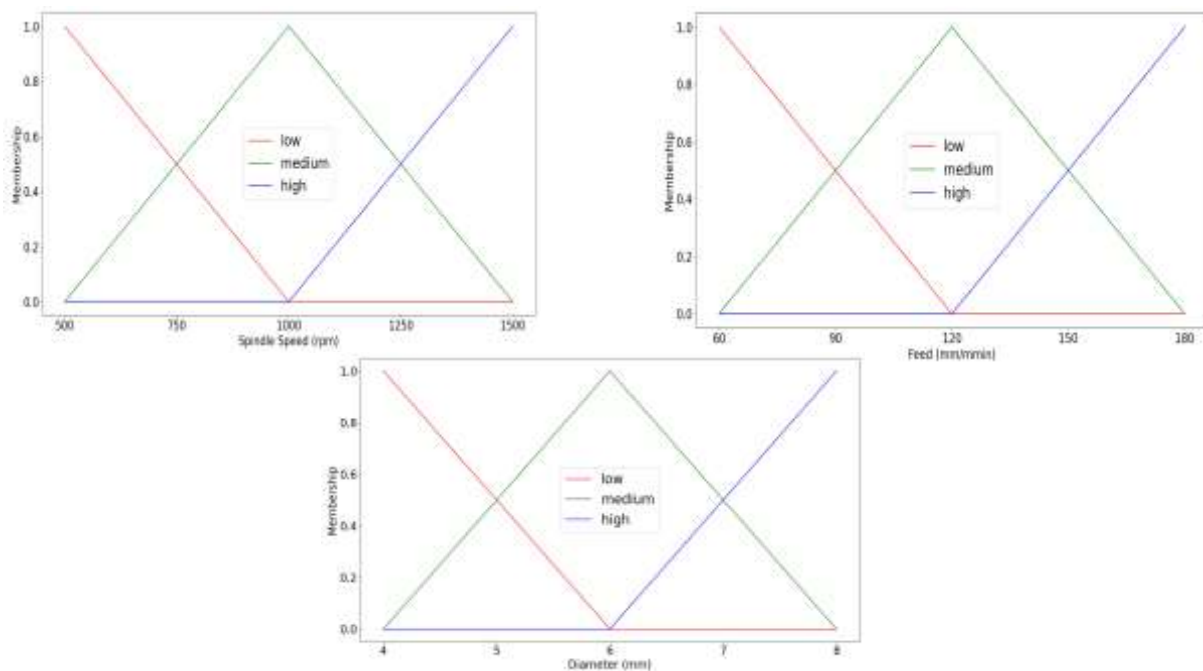

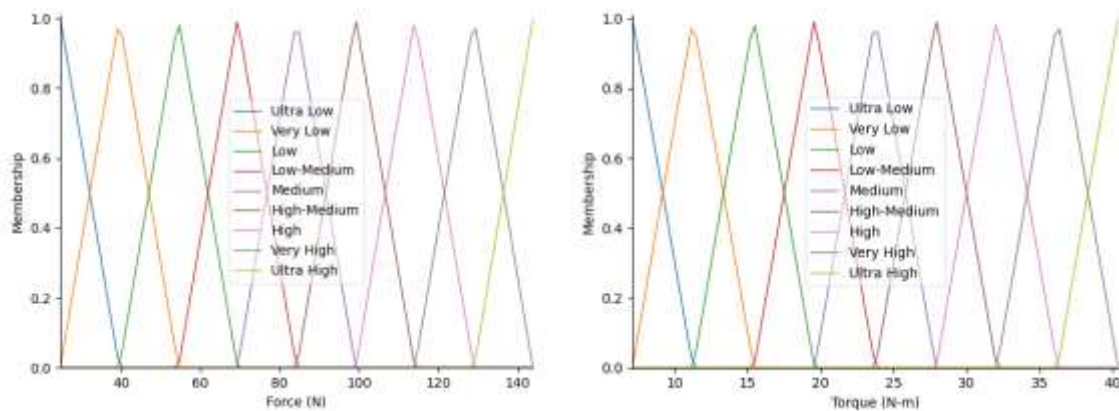Figure 4: Fuzzy membership functions for control parameters

Figure 5: Fuzzy membership functions for output parameters

4. Results and Discussion

The experimental values of thrust force and torque acting on the sample are given in table 4.

Table 4: Experimental Values for Thrust Force and Torque

S.No	Spindle Speed (rpm)	Feed Rate (mm/min)	Drill Diameter (mm)	Thrust Force (N)	Torque (N-m)
1	500	60	4	39.98	7.17
2	500	120	4	61.42	7.12
3	500	180	4	92.32	9.54
4	1000	60	4	26.09	11.28
5	1000	120	4	38.07	11.12
6	1000	180	4	48.45	11.29
7	1500	60	4	24.64	9
8	1500	120	4	29.07	10.27
9	1500	180	4	38.45	10.07
10	500	60	6	53.94	16.17
11	500	120	6	86.67	20.45
12	500	180	6	108.8	18.77
13	1000	60	6	38.68	18.77
14	1000	120	6	51.65	21.31
15	1000	180	6	65.77	19.99
16	1500	60	6	31.59	14.57
17	1500	120	6	45.47	19.3
18	1500	180	6	53.18	18.69
19	500	60	8	72.33	28.15
20	500	120	8	106	32.07
21	500	180	8	143.9	39.75
22	1000	60	8	55.39	23.5
23	1000	120	8	71.18	40.4
24	1000	180	8	83.62	31.59
25	1500	60	8	40.44	19.76
26	1500	120	8	58.14	37.78
27	1500	180	8	69.12	33.19

The values obtained were input into the FIS devised in Python, and the fuzzy mapping rules were defined based on the values observed. The general syntax of the rules was as follows

If Spindle Speed in [$SetS_1$] and Feed Rate in [$SetS_2$] and Drill Diameter in [$SetS_3$], then Thrust Force in [$SetO_1$]

If Spindle Speed in [$SetS_1$] and Feed Rate in [$SetS_2$] and Drill Diameter in [$SetS_3$], then Torque in [$SetO_1$]

After defining the rules to map every possible combination of input fuzzy sets to appropriate output fuzzy sets, the input values were fed to the model and the thrust force and torque were predicted. The predicted values and deviation from the observed values are given in table 5.

Table 5: Predicted Values and % error

S.No	Spindle Speed (rpm)	Feed Rate (mm/min)	Drill Diameter (mm)	Thrust Force (N)		Torque (N-m)	
				Prediction	%deviation	Prediction	%deviation
1	500	60	4	39.56	1.05	8.51	-18.66
2	500	120	4	54.45	11.35	8.51	-19.46
3	500	180	4	99.17	-7.42	8.51	-10.77
4	1000	60	4	29.62	-13.53	11.29	-0.09
5	1000	120	4	39.56	-3.91	11.29	-1.53
6	1000	180	4	54.45	-12.38	11.29	0.00
7	1500	60	4	29.62	-20.21	8.51	5.48
8	1500	120	4	29.62	-1.89	11.29	-9.94
9	1500	180	4	39.56	-2.89	11.29	-12.12
10	500	60	6	54.45	-0.95	15.44	4.51
11	500	120	6	84.27	2.77	19.60	4.16
12	500	180	6	114.09	-4.86	19.60	-4.42
13	1000	60	6	39.56	-2.28	19.60	-4.42
14	1000	120	6	54.45	-5.42	19.60	8.02
15	1000	180	6	69.37	-5.47	19.60	1.95
16	1500	60	6	39.56	-25.23	15.44	-5.97
17	1500	120	6	39.56	13.00	19.60	-1.55
18	1500	180	6	54.45	-2.39	19.60	-4.87
19	500	60	8	69.37	4.09	27.92	0.82
20	500	120	8	99.17	6.44	32.08	-0.03
21	500	180	8	138.92	3.46	39.01	1.86
22	1000	60	8	54.45	1.70	23.76	-1.11
23	1000	120	8	69.37	2.54	39.01	3.44
24	1000	180	8	84.27	-0.78	27.92	11.62
25	1500	60	8	39.56	2.18	11.29	42.86
26	1500	120	8	54.45	6.35	36.24	4.08
27	1500	180	8	69.37	-0.36	32.08	3.34
				Mean error	-2.03	**Mean error**	0.69

Line graphs were drawn by overlaying the experimental values with the predicted ones for each experiment trial. The plots are shown in figure 6.
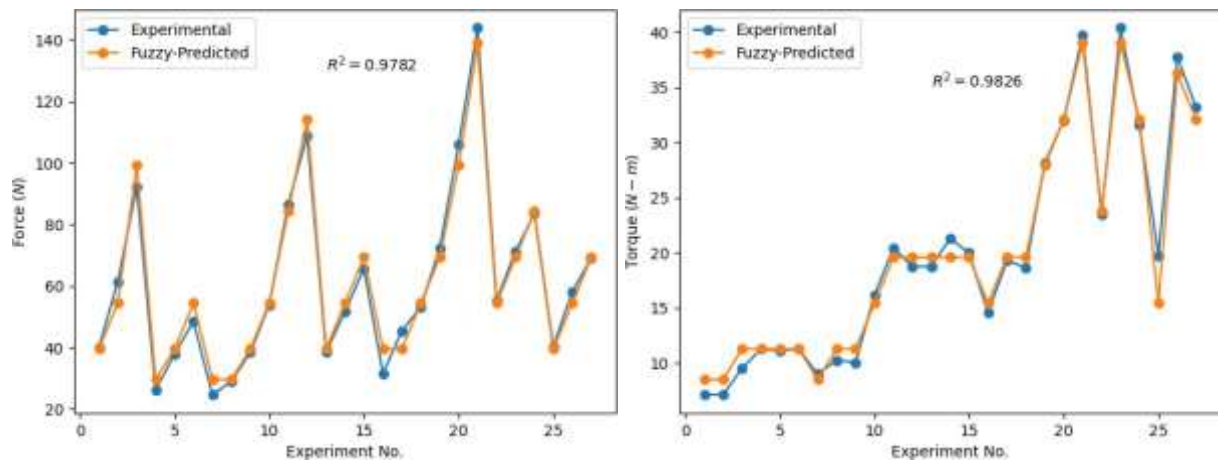
Figure 6: Comparison of experimental values and values predicted by the fuzzy model

The figures indicate a relatively predictable variation in thrust force and torque with the control parameters, namely drill bit diameter (mm), spindle speed (rpm) and feed rate (mm/min). The thrust force appears to vary directly with feed rate and drill bit diameter, and inversely with spindle speed, while the torque appears to generally increase with spindle speed and feed rate. This observation is in agreement with the results of the work done by Nagarajan et al[9].

A more thorough comparison is made by producing scatter plots between the experimental and predicted values, and fitting a linear trend curve. A bar chart comparison of 5 randomly selected data points (to eliminate the possibility of spurious correlations) is also done for better corroboration. The goodness of fit of the model to the data is apparent in the plots, which are shown in figures 7 and 8.
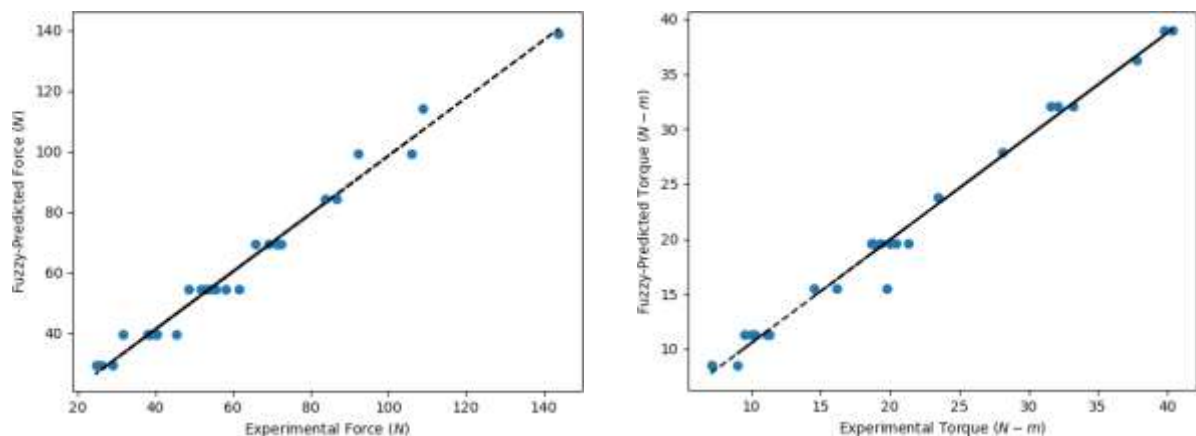

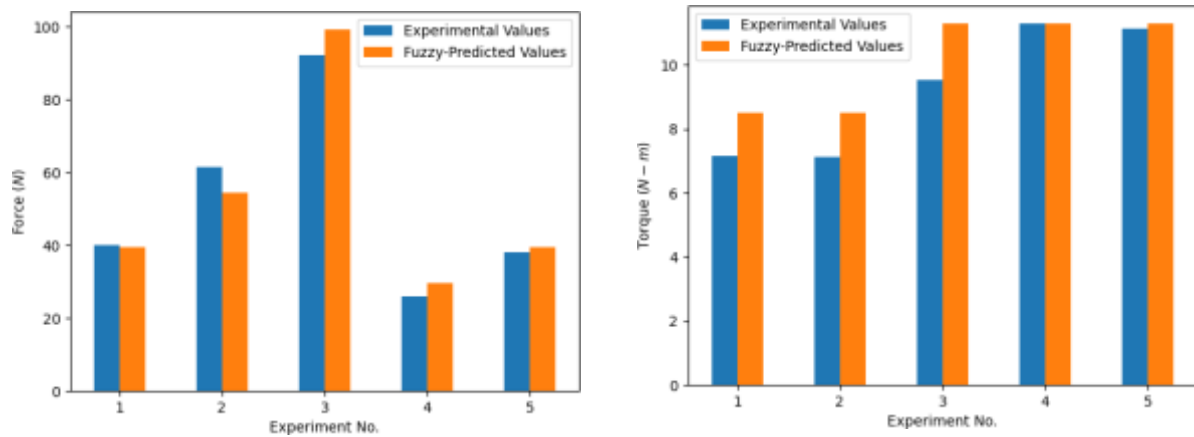Figure 7: Trend line between experimental and predicted values

Figure 8: Examination of randomly chosen experimental trials

In order to compare the capabilities of the skfuzzy module in Python with the more popular Fuzzy Logic Toolbox in MATLAB, the same model was created using that toolbox in MATLAB and the experimental values were used to train it. A comparison between the predicted results obtained in each case and the experimental results was made. The plots obtained in the comparison are shown below in figure 9.
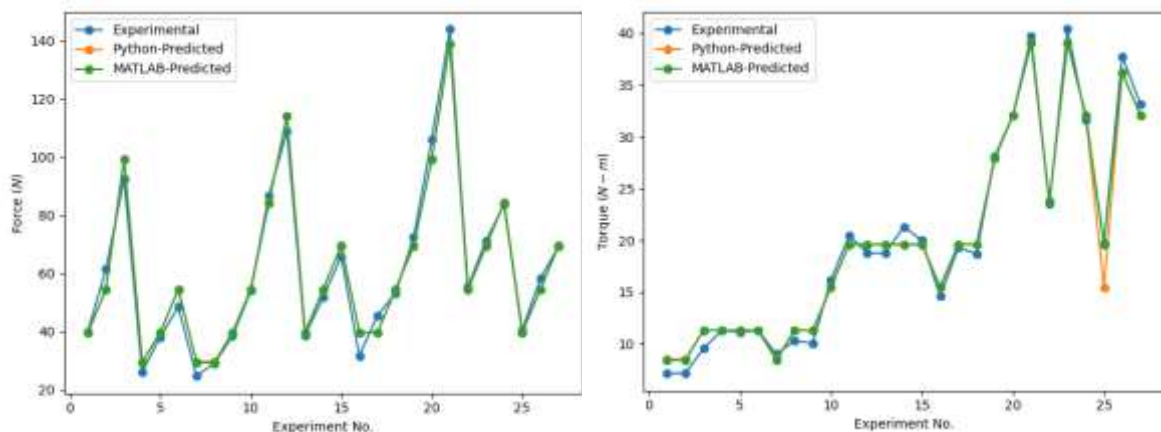

Figure 9: Comparison of Python skfuzzy module and MATLAB Fuzzy Logic Toolbox

The plots make it clear that although both tools are very good predictors of the output values, the Fuzzy Logic Toolbox has a slight edge over the skfuzzy module, and it seems to be able to better handle the random variations of the output, especially in the case of the torque prediction, which may be attributed to the higher computational suitability and capacity of MATLAB in general. This is further quantitatively demonstrated by calculating the R^2 correlation coefficient in each case. The obtained values are given in table 6.

Table 6: Comparison of Python model with MATLAB model

S. No	Predicted Quantity	Correlation R^2 with experimental values	
		Python FIS	MATLAB FIS
1	Thrust Force (N)	0.9782	0.9801
2	Torque (N-m)	0.9826	0.9915

The obtained values are very close to 1 in using both the Python and MATLAB models, indicating that the model can account for virtually all unpredictability occurring in the system.

5. Conclusions and Future Work

In summary, drilling tests were conducted on glass-flax-hemp fiber hybrid composite fabricated with the hand-layup process. From previous work, the significant control parameters to be analyzed were chosen to be the spindle speed, feed rate and drill bit diameter. Experiment design and assignment of control parameters was done using a Taguchi L_{27} orthogonal array. Experimentally measured values of thrust force and torque acting on the composite sample were recorded, and a fuzzy-logic inference system (FIS) composed of 3 inputs, 2 outputs and 54 rule sets was designed in Python to make predictions for the same.

The FIS model was found to have near-perfect correlation with experimentally obtained values of thrust force and torque, thus establishing its suitability for use in modelling of drilling parameters for HFCs. The modelling process can be used to reduce the chance of damage of the composite sample during drilling in the way of delamination and internal cracks caused due to excessive thrust force and torque.

The high degree of correlation observed between the values with minimal computational effort in the model suggests that this technique can be used for other composite materials than the one under study. Obviously, the specific interactions between the input and output parameters and the fuzzy rules for mapping will vary from one material to another, but the general principles of the fuzzy logic modelling can still be applied to any composite by collecting enough data for training.

For better performance of the model, but at the risk of over-fitting, more process parameters such as coolant use, heat generated etc. can be integrated into the model; also, the membership functions for inputs and outputs can be further granularized for better results at the added expense of computational complexity. Further, the nature of the membership functions used can be varied and the effect on the computational efficiency of the predictive model could be studied. For instance, instead of using triangular membership functions, trapezoidal or Gaussian bell-curve membership functions could be considered.

In this work, only three levels of variation were considered for each input parameter taken. In forthcoming work, the range of input parameters considered could be widened (e.g. spindle speeds of 2000 and 2500 rpm may be included). It is also possible to conduct tests and perform modelling for different composite samples and engage in a differential study, analyzing the input-output interactions for each sample and noting the influence of other possible significant control parameters.

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