Optimizing Machining Parameters for Drilling Carbon Fibre Epoxy Material with Python's Linear Regression Model.

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Abstract: The usage of composite materials has increased across many industries, especially aerospace, due to their exceptional mechanical properties. While drilling is a common method for putting these composites together, it can lead to damage like delamination. For this damage to be avoided, it is essential to use the proper drilling process parameters and tool design. In order to predict the drilling force at which delamination occurs, developed a novel mathematical model in this study. For unidirectional composites, the model accounts for the thermal, mechanical, and kind of fracture that occurs in the delamination region. The proposed model was shown to be more accurate when compared to older models. The present work is also looked into how planning feed rates and drill bit design might reduce delamination. And found that by adjusting the chisel edge ratio according to the geometry of the drill bit, it is possible to predict a thrust force that is more accurately adequate to reduce delamination. The results of this study can be used as a reference to improve the utilization of accessible resources and machining equipment while maintaining the quality of drilled holes in composite materials. The machining input parameters, such as spindle speed, feed rate, and fibre orientation angle, must be optimized in order to solve these issues. In this article, the optimal machining input parameters for drilling Carbon **Fibre** Reinforced Polymer (CFRP) material could be determined using a linear regression model and python programming.

Keywords: CFRP laminates, delamination, drilling, critical thrust force, Python programming.

I. INTRODUCTION

Drilling holes are frequently needed in the aerospace and automotive industries to join different material components. In contrast to the 250 million twist drill bits used annually by the US aircraft sector alone, it is anticipated that 55,000 holes are drilled for each airbus A350 unit. However, Zitoune et al [3] research demonstrates that composite plates with drilled or moulded holes can absorb damage, resulting in a 30% drop in fracture strength when parts are put under stress.

Molded holes aren't always an option, and drilling could be more challenging while still adhering to the essential size and positioning restrictions. This fuels the need to improve the drilling process. Contrary to ductile metals, Carbon Fibre Reinforced Polymers (CFRPs) are prone to brittle fracture propagation [4, 5]. As a result, drilling CFRPs may result in negative effects on the workpiece, such as ply delamination, due to the drill's considerable thrust power. As drilling starts, the workpiece initially resists the thrust force created by the tool's chisel edge. When the drill approaches the exit surface, there is less material available to support the thrust force, which results in a significant thrust force being transferred to the interface between the plies. This causes delamination when bending is all that is applied. In order to lessen delamination, it is important to drill at a different feed rate and to calculate the critical thrust power in relation to the laminate's uncut thickness. An aggressive feed rate should be utilized near the hole entry to promote the Material Removal Rate (MRR), whereas a lesser feed rate should be used close to the cut's exit to reduce delamination [6].

Moreover, tool wear makes drilling more dynamic. According to Ismail et al., [7], this is an unavoidable phenomenon that necessitates the use of coolants, tool life monitoring and forecast, effective drill design geometry, and perfect process parameters. Vijayaraghvan discusses numerous aspects of modelling multilayer material machining, including contact, fracture criteria, adaptive meshing, element types, and tool modelling [8]. Several studies have been conducted on drilling CFRP materials, including reviews by Panchagnula et al. [9] and Lissek et al. [10], both of which emphasize the significance of process monitoring to ensure hole quality. According to Kahwash et al. [11], 2D orthogonal cutting is currently utilised to describe the cutting process of CFRPs since it is straightforward and has a computational advantage. Liu et al. came to the conclusion that the elastic modulus differences between the materials had an effect on the drilled hole sizes using experimental data on drilling composite laminates [12Mahdi et al. used computing to study the effects of mesh sensitivity, rake angle, and thrust versus strain in the plane. The results showed that the rake angle had no effect. There have been effective demonstrations of how the fibre angle affects FRP machining [13]. According to Shyha et al., the two most important machining process parameters when drilling CFRPs are drill geometry and feed rate [14]. Faraz et al. looked into the effects of cutting-edge rounding in order to predict, prevent, and preserve hole quality [2]. This project's objective was to promote the development of a FE drilling model that would be used as a tool to quickly and accurately assess various drill geometries. [15,16]. Experimental research was conducted to examine the effect of drilling forces on hole quality in order to confirm the accuracy of the predictions generated by the FE model.

Understanding the various levels of cutting circumstances is necessary to optimise the drilling of CFRP composites' machining characteristics. There needs to be a lot of research done to identify the ideal values. For manufacturing operations to be more productive, effective, and high-quality, machining parameters must be optimised. Unlike earlier research, the goal of this one was to show how Python and a linear regression model can predict the best machining parameters and explain how they may be used in real-world situations. Three alternative feed and spindle speeds, fibre orientations, and thrust, torque, and delamination in and out measurements were made while drilling to form the Taguchi experiment set for this purpose.

II. MATERIALS METHODS

This study used a hand lay- up (at 30°, 45°, and 60°) approach to drill into CFRP plates and CFRP plates 250 mm x 200 mm x 3 mm, containing nano particles (Tio2) constructed of unidirectional carbon fibre and epoxy resin. Cutting speed, feed rate, and fibre orientation are taken into consideration; Table 1 lists the cutting parameters for the experiments, which were carried out using a CNC machine as shown in figure 1. Thrust force, torque, delamination factor at entry, and delamination factor at exit, respectively, are the actions conducted following machining. The force acting on the cutting tool was recorded with a dynamometer mounted to the CNC drilling machine. The drill bit is used for the experimentation is shown in figure2 having 5mm diameter. The MINITAB software was used to assess the data, and its formulas were used to compute the delamination factor at both entry and exit for every combination of the design matrix. The probabilistic design matrix used in the present investigation was derived from the Taguchi orthogonal array.There are nine different combinations of settings for the feed rate, cutting speed, and fibre orientation represented in table 2. Table 3, lists the thrust force, and delamination factor at entry F_D (in) and exit F_D (out) for each combination of the design matrix. The experimental runs allowed for the calculation of the impacts of the process parameters on the thrust force, torque, and entry delamination factor on a linear, quadratic, and two-way interactive basis.

Fig1: Experimental setup

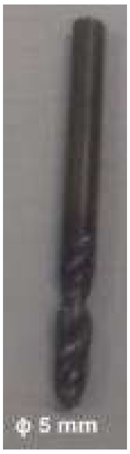


Fig 2: Drill bit of 5mm

A linear regression model has been used to find the ideal machining input parameters and expected values.

The input and output parameters are first imported into a Python panda data frame. Then, separate the input and output variables and divide the data into training and testing sets using the train test split function from the sci-kit-learn library. 20% of the data are used for testing, while the remaining 80% are used for training.

The training data is then fitted to a linear regression model was developed. Finally, forecast the output variables with brand-new input data using the predict function.

Table1: CFRP plate specifications.

Specification/Description	Value(s)
Density	2.2 g/cm^3
Method of formation	Hand- layup
Orientation	30,45 & 60^0
Construction	carbon fibre + Epoxy
Fibre and matrix % ratio	Fibre: Epoxy = 60:40

Table2: Experimentation domain:

Parameters (Notation)	Unit	Level 1	Level 2	Level 3
Spindle Speed (N)	Rpm	1000	1200	1400
Feed rate (f)	mm/min	100	150	200
Fibre orientation	Degrees	30	45	60

Table3: Design of experiments and S/N ratio's for output responses

Sl.No.	**Spindle Speed (RPM)**	**Feed (mm/min)**	**Fibre orientation (angle)**	**Thrust**	**S/N ratio for Thrust**	**F_D (in)**	**S/N ratio for F_D (in)**	**F_D (out)**	**S/N ratio for F_D (out)**
1	1000	100	30	0.061	25.32	1.072	-0.592	1.069	-0.645
2	1000	150	45	0.069	23.96	1.364	-2.846	1.168	-1.412
3	1000	200	60	0. 1	21.03	1.624	-3.924	1.298	-2.496
3	1200	100	45	0.0712	24.17	1.386	-2.795	1.19	-1.552
5	1200	150	60	0.11	20.24	1.625	-3.983	1.315	-2.283
6	1200	200	30	0.058	25.67	1.074	-0.924	1.082	-0.685
7	1400	100	60	0.071	23.95	1.513	-3.881	1.31	-2.632
8	1400	150	30	0.132	18.15	1.05	-0.528	1.1	-0.697
9	1400	200	45	0.139	17.84	1.314	-2.612	1.175	-1.584

III. RESULTS AND DISCUSSIONS

Statistical evaluation:

The models' suitability was evaluated using (ANOVA). According to this method, (i) the estimated F-ratio of the constructed model should not be greater than the standard tabulated value of F-ratio for a desired degree of confidence (95%). and (ii) the model may be considered adequate within the confidence inhibit if the calculated R-ratio of the developed model exceeds the standard tabulated value of the R-ratio for a desired level of confidence (95%). Analysis of Variance for output responses (Thrust, F_D (in), F_D (out)) are presented in following tables. For analyze the Taguchi's technique perform the experiments lower-the-better.

Table 4: Analysis of Variance for Thrust versus speed, feed rate, fibre orientation.

Analysis of Variance for Thrust versus Speed, Feed, Fibre orientation							
Source	**DF**	**SeqSS**	**AdjSS**	**AdjMS**	**F**	**P**	**% Contribution**
Spindle speed	2	29.134	29.134	14.567	2.32	0.086	34.14
Feed rate	2	27.245	27.245	13.6225	1.06	0.094	30.87
Fibre orientation	2	18.421	18.421	9.2105	0.82	0.619	21.7
Residual Error	2	10.124	10.124	5.062			
Total	8	84.924					

Table 5: Analysis of Variance for F_D (in) versus speed, feed rate, and fibre orientation

Analysis of Variance for F_D (in) versus Speed, Feed, Fibre orientation							
Source	**DF**	**Seq SS**	**AdjSS**	**AdjMS**	**F**	**P**	**% Contribution**
Spindle speed	2	0.0242	0.0242	0.0121	10.64	0.16	1.2
Feed rate	2	0.035	0.035	0.0173	3.9	0.18	2.56
Fibre orientation	2	13.214	13.214	6.712	3.45	0.03	95.26
Residual Error	2	0.0078	0.0078	0.0039			
Total	8	13.9449					

Table 6: Analysis of Variance for F_D (out) versus speed, feed rate, and fibre orientation

Analysis of Variance for F_D (out) versus Speed, Feed, Fibre orientation							
Source	**DF**	**Seq SS**	**AdjSS**	**AdjMS**	**F**	**P**	**% Contribution**
Spindle speed	2	0.01284	0.01284	0.00642	1.2	0.327	2.7
Feed rate	2	0.04384	0.04384	0.02192	2.3	0.124	1.1
Fibre orientation	2	3.6548	3.6548	1.8274	212.4	0.035	95.12
Residual Error	2	0.01238	0.01238	0.00619			
Total	8	3.72386					

From the ANOVA table, 4, 5, and 6, p value is <0.05, it indicates that the fibre orientation is highly influenced by drilling process parameters. And percentage contribution is also more for fibre orientation is 95.26% and 95.12% respectively. The regression analysis summery is listed in table7, 8, and9.

Regression analysis is a statistical method used to estimate the relationships between variables in statistics. When the focus is on the link between a dependent variable and one or more independent variables, it encompasses numerous approaches for modelling and analyzing multiple variables.

Table 7: Regression Analysis: Thrust versus Feed, fibre orientation, c

Model Summary	**S**	**R-sq**	**R-sq(adj)**	**R-sq(pred)**
	0.02863	50.09%	20.15%	0.00%

Table 8: Regression Analysis: F_D (in) versus Speed, Feed, fibre orientation

Model Summary	**S**	**R-sq**	**R-sq(adj)**	**R-sq(pred)**
	0.01189	95.26%	94.56%	96.79%

Table 9: Regression Analysis: F_D (out) versus Speed, Feed, fibre orientation

Model Summary	**S**	**R-sq**	**R-sq(adj)**	**R-sq(pred)**
	0.01211	95.12%	96.16%	95.8%

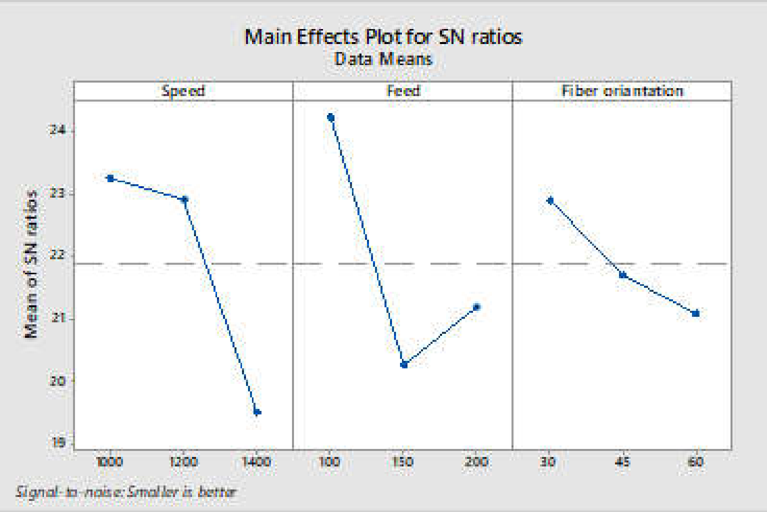


Fig.3.Main effects plot for SN ratios for Thrust

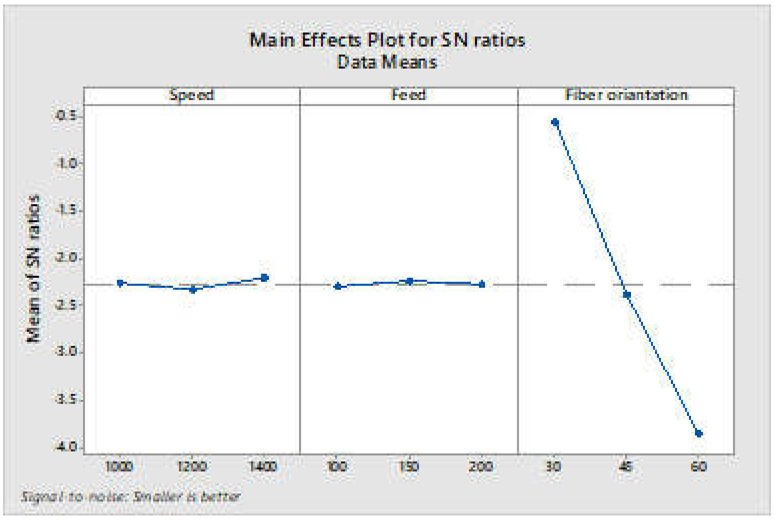


Fig.4.Main effects plot for SN ratios for peel-up delamination F_D(in)

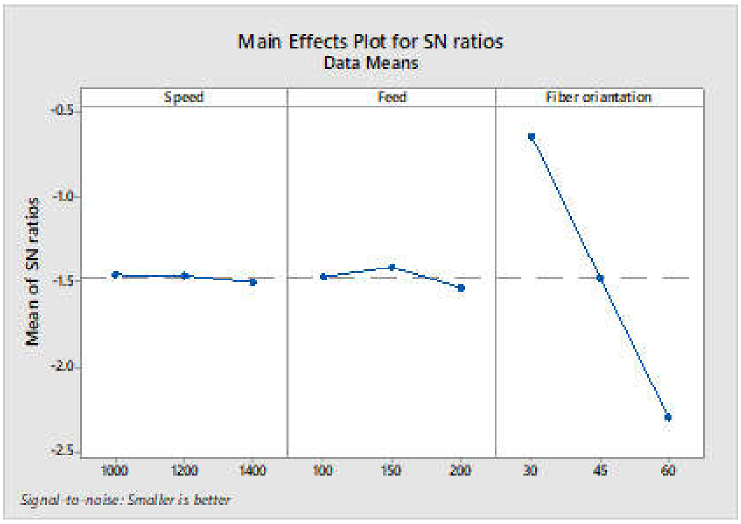
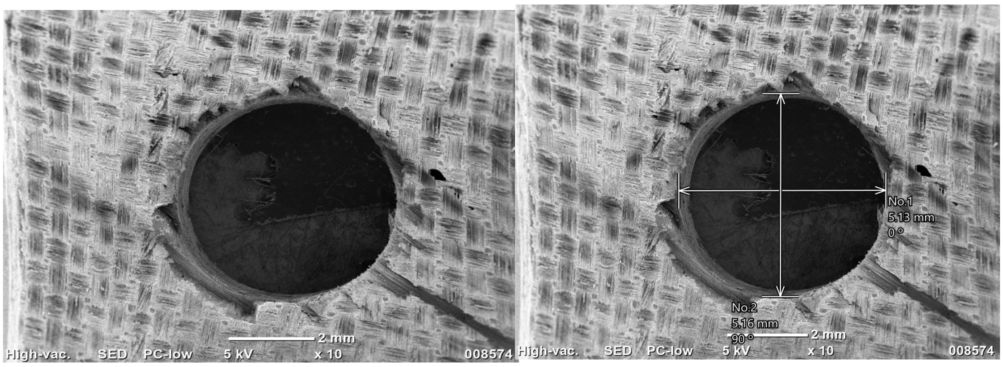


Fig.5.Main effects plot for SN ratios for pepush down delamination F_D(out)

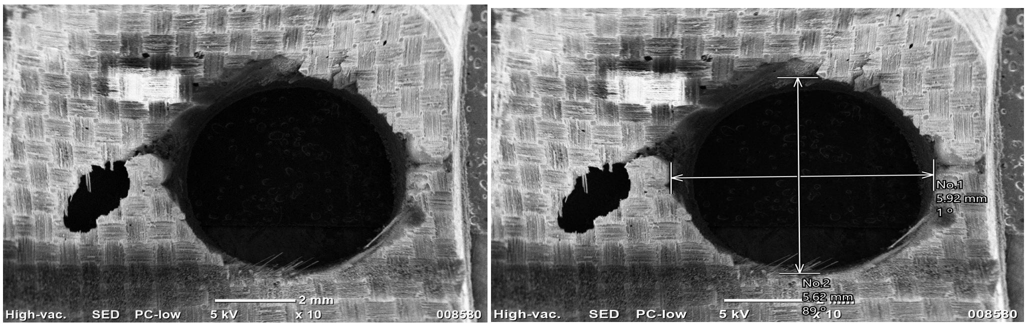
SEM evaluation:

A potent method for analyzing the microstructure and superior surface quality of laminated materials is scanning electron microscopy (SEM) [17]. Let's talk about the superior drilling surface of carbon fibre epoxy substance.



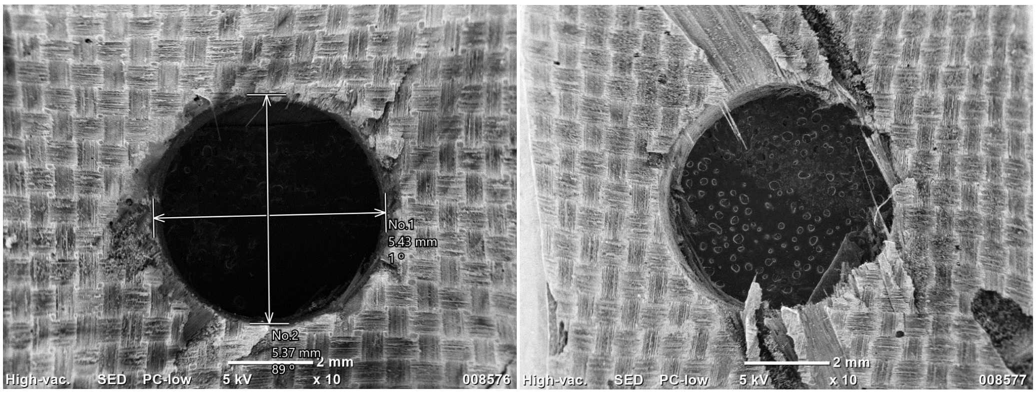
(a) (b)

Figure.6. CFRP Specimen at (a) Entry (b) Exit with fibre Orientation of 30^0



(a) (b)

Figure.7. CFRP Specimen at (a) Entry (b) Exit with fibre Orientation of 45^0



(a) (b)

Figure.8. CFRP Specimen at (a) Entry (b) Exit with fibre Orientation of 60^0

Due to strong tensile cutting forces in the tool advancement mechanism, inter-laminar shear stresses were seen at the fibre-matrix interface. Significant damage was observed, including matrix cracks, delamination, fibre bending, and fibre bending. The surface failures, such as cracks in the matrix and fibre fractures, are depicted in Figure 6(a) with higher thrust forces.

The matrix fracture was complex and elastic healing was challenging, resulting in bigger chip fragments. The cutting operation got more difficult, noticeably larger chips were produced; tool clogging and a complex process for chip production appeared. Additionally, there were other subsurface problems and fibre pullouts. The surface texture deteriorated and the surface that was machined became asymmetrical. Furthermore, delamination appeared and the machined surface got rougher. Figure 6(b), which describes failure mechanisms such fibre pullout and subsurface damages, demonstrates the failure mechanism.

The machining circumstances are provided in Table 3 (trial numbers 3 to 5), and they reveal that the work piece is quickly pierced over 1200 rpm when employing tool at higher spindle speeds of 1400 rpm. The work piece and the tool rake face experienced significant friction. Shear zone rubbing occurred as a result of increasing thrusting forces. As a result, fibres have a tendency to bend too quickly and break. Maximum delamination was clearly attained at 1.31. Damage mechanisms brought on by matrix infusion and fibre compression are depicted in Figure 7 (a, and b).

Maximum spindle speed resulted in significant friction and subsequent thermal strains. It caused an issue with tool clogging that needed to be rectified by tool plowing on the milling surface. As a result, as the tool moved in the direction of the work piece's rake face, glass resin, and fibre were broken. Greater thrusting caused thermo-mechanical activity, which in turn caused friction at the interface of the tool and workpiece because of the tool's vigorous plowing action on the fibres. This surface texture was subpar due to the delamination (1.315). Smears in the glass resin and fibre breakage are depicted in Figure 8(a, and b).

Confirmation tests:

MINITAB 17 was useful to know predict values of optimal setting parameters for output responses with SN ratios. Conducting three experiments from each optimal set of parameters to validate the predicted values and arranged in table 10, 11, and 12.

Table 10: Prediction for Thrust

Fit	SE Fit	95% CI	95% PI
0.0439167	0.0223781	(-0.0136081, 0.101441)	(-0.0494856, 0.137319)

Table 11: Prediction for F_D (in)

Fit	SE Fit	95% CI	95% PI
1.074	0.0073666	(1.05506, 1.09294)	(1.04325, 1.10475)

Table 12: Prediction for F_D (out)

Fit	SE Fit	95% CI	95% PI
1.06808	0.0092944	(1.04419, 1.09198)	(1.02929, 1.10688)

Regression equation using MINITAB software:

Regression analysis for thrust versus feed, fibre orientation, c

Regression Equation is:

Thrust = -0.0995 + 0.000398 * Feed + 0.000352 * Fibre orientation + 0.000121

Regression analysis for F_D (in) versus feed, fibre orientation, c

Regression Equation is:

F_D (in) = 0.7012 - 0.000052 * Feed + 0.018700 * Fibre orientation - 0.000030 speed

Regression analysis for F_D (out) versus feed, fibre orientation, c

Regression Equation is: F_D (out) = 0.8642 + 0.000090 * Feed + 0.008181 *Fibre orientation + 0.000014 speed

Python programming for optimizing machining parameters during drilling:

```
import pandas as pd

from sklearn.linear_model import LinearRegression

from sklearn.model_selection import train_test_split

# load data into pandas dataframe
```

```
data = pd.DataFrame({
   'Speed_Rpm': [1000, 1000, 1000, 1200, 1200, 1200, 1400, 1400, 1400],
   'Feed_mm_min': [100, 150, 200, 100, 150, 200, 100, 150, 200],
   'Fibre_Orientation_angle': [30, 45, 60, 45, 60, 30, 60, 30, 45],
   'Thrust_kN': [0.054, 0.065, 0.093, 0.0635, 0.109, 0.053, 0.068, 0.129, 0.135],
   'Torque_MpakN_mm': [0.37, 0.4, 0.355, 0.46, 0.55775, 0.44, 0.2875, 0.33, 0.295],
   'Fd_in': [1.068, 1.315, 1.558, 1.328, 1.562, 1.078, 1.557, 1.055, 1.305],
   'Fd_out': [1.072, 1.17, 1.319, 1.192, 1.2905, 1.077, 1.301, 1.08, 1.195]
})
# separate input and output variables
X = data[['Speed_Rpm', 'Feed_mm_min', 'Fibre_orientation_angle']]
y = data[['Thrust_kN', 'Fd_in', 'Fd_out']]
# split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# create linear regression model and fit to training data
model = LinearRegression()
model.fit(X_train, y_train)
# predict output variables for new input variables
new_X = [[1100, 175, 40], [1300, 125, 50], [1500, 175, 35]]
new_y = model.predict (new_X)
print(new_y)
```

Output:optimize Delamination factor

```
Array ([[0.0819919, 1.29718349, 1.24294187],
    [0.11814127, 1.25428326, 1.18958736],
    [0.12142598, 1.34254105, 1.30336158]])
```

The estimated values for drilling CFRP material as well as the optimized machining input parameters are included in the Python code's output. The intended values for each set of given variables are thrust, F_D (in), and F_D (out), in that order. For instance, we can predict the thrust, F_D (in), and F_D (out) values when drilling CFRP material at 1200 RPM, 175 mm/min, and a fibre orientation angle of 45^0 with the linear regression approach. The anticipated values are 0.0819587 kN, 1.24215834, and 1.24294182, respectively. Along with the ideal machining input parameters, we can also predict the values of other sets of input parameters.

IV. CONCLUSION

In the present study, the drilling surface quality of CFRP composite laminates has been studied as well as tool performance and the effect of input process parameters. The experiments' results were assessed and correlated using SEM microscopy, variable effect graphical representations, and other methods. Here is a summary of the results:

1) The results show that for the thrust parameter, spindle speed has the highest effect is 34.14%, followed by feed rate is 30.85%, and fibre orientation is 21.7%. On the other hand, for the delamination factor at entry, fibre orientation has the highest effect is 95.26%, followed by feed rate is 2.56%, and speed is 1.2%. For the delamination factor at exit, fibre orientation still has the highest effect is 95.12%, followed by speed is 2.7%, and feed is 1.1%. According to the Taguchi technique of optimization, thrust is the significant response for fibre orientation and feed rate and speed.

2) The SEM evaluation of composites made of CFRP based on drilling surface characteristics in different phases is provided below.

- From SEM figures 6(a, b), 7(a, b), and 8(a, b), the peel-up delamination, and push-down delamination is more dominated for the fibre orientation of the drilled laminate is 60^0.
- From the SEM observation, the damage mechanism is more conquered by fibre orientation followed by spindle speed, and feed rate.

3) When compared to the experiments, the expected outcome is validated. Thus, the effectiveness of the optimal circumstances obtained is confirmed. The results showed how well the linear regression model and Python programming performed in identifying the ideal input variables and output values for drilling CFRP material. Businesses and industrial sectors involved in secondary manufacturing may find this study is useful.

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