Journal of Mines, Metals and Fuels, *73(10): 3333-3343; 2025. DOI: 10.18311/jmmf/2025/49071*

Online ISSN : 0022-2755

Journal of Mines, Metals and Fuels

Contents available at: *www.informaticsjournals.co.in/index.php/jmmf*

Optimization of Machining Process Parameters for E-Glass/Jute Fiber Composites Using Response Surface Methodology for E- Vehicle Application

Mahendra Kumar Malviya[1]*, Utsav Mahobiya[2], Nishant Dwivedi[3], Pavan Mehta[3] and Gurjeet Singh[4]

[1]*Department of Mechanical Engineering, Government Polytechnic College, Betul - 461001 Madhya Pradesh, India; mkmalviya1@gmail.com*

[2]*Department of Mechanical Engineering, Corporate Institute of Science and Technology, Bhopal - 462022, Madhya Pradesh, India*

[3]*Department of Electrical Engineering, Medicaps University, Indore - 453331, Madhya Pradesh, India*

[4]*Department of Mechanical Engineering, IES College of Technology, Bhopal - 462042, Madhya Pradesh, India*

Abstract

Fibre-reinforced composites have gained popularity because of the increased need for lightweight, high-strength materials in the production of electric vehicles (E-vehicles). Optimising the machining process parameters for E-Glass/Jute fibre composites is crucial for enhancing their machinability in structural components of E-vehicles. Response Surface Methodology (RSM) is used in this work to identify the ideal control settings for feed rate, spindle speed, depth of cut, and their impacts on Material Removal Rate (MRR) and Surface Roughness (SR). To forecast these machining responses, a mathematical model was created. The results of the investigation showed that surface quality was significantly affected by feed rate and depth of cut. The parametric study indicated that both surface quality and MRR increased with higher feed rates, whereas surface quality exhibited a declining trend with an increasing depth of cut. The results offer important information about how to increase the machining efficiency of E-Glass/Jute fibre composites, which makes them appropriate for high-strength, lightweight structural elements in E-vehicle applications.

Major Findings: *The study found that feed rate and depth of cut significantly influence surface quality in machining E-Glass/Jute fibre composites. Higher feed rates improved both MRR and surface roughness, whereas increasing depth of cut led to a decline in surface quality.*

Keywords: *E-Glass/Jute Fiber Composites, Machining Parameter Optimization, MRR, RSM, SR*

1.0 Introduction

Hybrid fibre-reinforced composites have gained popularity as a result of the automotive industry's growing need for lightweight, high-strength materials, particularly for electric vehicles (EVs). Among these materials, E-glass/jute fibre-reinforced epoxy composites have garnered considerable attention due to their advantageous mechanical properties, cost efficiency, and environmental sustainability[1-3]. Use of Glass/jute fibre composite for engineering applications, such as in electric vehicles, is increasing as it reduces gross weight, but it sometimes demands machining or even joining[4]. As E-glass/jute fibre composites are non-conducting material, so can't

*Author for correspondence

be machined by non-traditional machining processes[5]. Further, these techniques are not suitable and cost-effective. Machining is the most widely used conventional method for generating circular surfaces at low cost and can be the best method for machining epoxy composites, as material removal is due to shearing. The most general and important quantifying parameters in machining are surface roughness and material removal rate. Surface roughness is a crucial aspect of the machining process, serving as a key indicator of product quality[6]. It measures the finer irregularities in the surface texture and is essential for achieving the desired surface quality, which directly impacts the functional performance of a part. Surface roughness plays a significant role in the performance of mechanical components and influences their production and operational costs, as it affects factors such as friction, ease of clamping, lubrication, electrical and thermal conductivity, and geometric tolerances, among others[7]. The ability of a manufacturing process to achieve the desired surface finish is influenced by various factors, including machining parameters, tool and workpiece material properties, and cutting conditions. Even small changes in any of the above-mentioned factors may have a significant effect on the produced surface quality. A good-quality machining surface can lead to improvement in physical properties of components such as fatigue strength, corrosion resistance and thermal resistance. Therefore, it is important for the researchers to model and quantify the relationship between roughness and the parameters affecting its value. Design methods such as factorial designs[8], and L9 orthogonal array[9,10] methods are now widely applied in place of the conventional experimental method of varying a single variable at a time, as considerable cost is saved in manufacturing and experimentation.

Several studies are available in the open literature that explore the impact of machining parameters on surface roughness and MRR of fibre-reinforced plastics, particularly focusing on glass fibre[11] and carbon fibre-reinforced plastic composites[12]. This includes drilling[13], milling, etc. Some natural fibre-reinforced epoxy composite was also machined by conventional methods[14]. Unconventional high heating rate methods, such as laser, are also used for cutting/machining of epoxy composite. The literature suggests that machining parameters, especially the feed rate, depth of cut and spindle speed, are important parameters to govern the output quality characteristics of the turned component[15]. The present work aims to optimise machining parameters for machining of unfilled epoxy using response surface methodology and ANOVA.

From the extensive literature survey, it is evident that machining fibre composites is a challenging operation due to the unique characteristics of these materials, such as their heterogeneity, anisotropy, and potential for fibre breakage. While suitable material selection, proper combination of machining process parameters, and the use of optimisation techniques are essential for achieving good, machined surfaces, significant gaps still exist in optimising machining processes for natural fibre and hybrid fibre composites. Most of the existing studies primarily focus on turning investigations involving either single or hybrid polymer composites, with limited research specifically addressing natural fibre composites or those reinforced with glass fibres and nanoclay. Furthermore, while optimisation techniques such as Response Surface Methodology (RSM) have been widely employed for polymer composites, their application to composites containing natural fibres and varying percentages of nano clay is still under-explored.

The present study aims to bridge this gap by investigating the turning operations of natural fibres and glass fibre reinforced composites, with varying additions of nano clay, to optimise cutting speed, feed rate, and depth of cut. This research will further develop mathematical models using RSM to predict and correlate the effects of these parameters on surface roughness and machining performance. Additionally, Signal-to-Noise (S/N) ratio and ANOVA analyses will be utilised to determine the most influential factors among the selected process parameters, ultimately contributing to the optimisation of surface quality and machining efficiency for fibre-reinforced composite materials. By addressing these gaps, this study seeks to enhance the understanding and applicability of machining techniques for hybrid and natural fibre composite materials in various industrial applications.

2.0 Experimentation

The binding material was prepared by mixing resin and hardener. The hardener was first mixed with the resin, and

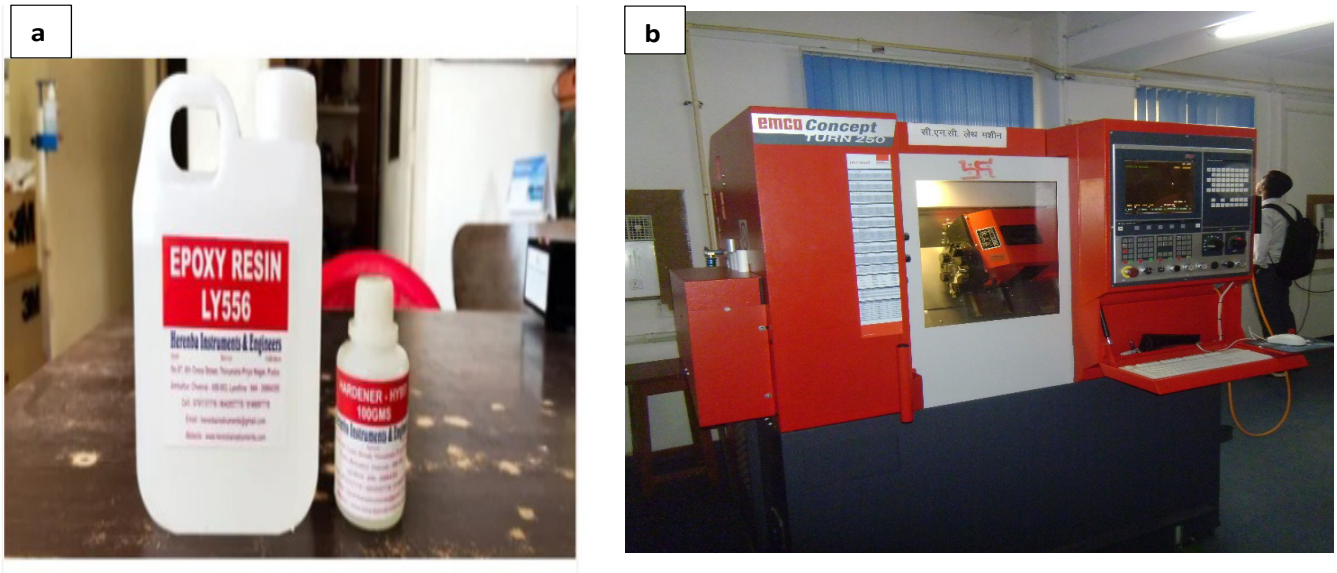


Figure 1. **(a)** Epoxy and Hardener and **(b)** CNC lathe machine.

then it was stirred well using a manual stirrer. The mixed resin had a setting time of 40 minutes. So, as soon as the resin mixture is prepared, it should be used quickly to act as a binder as shown in Figure 1(a). The mixing ratio was kept constant as 1:10, i.e hardener: epoxy. After mixing, the epoxy + hardener was transferred into a vertical cast iron mould of circular cross section of diameter 20 mm to cast epoxy cylinders as shown in Figure 1(b). A total of 15 such epoxy cylinders were cast for turning.

The experimental trials of machining were conducted on a CNC lathe machine, having an automatic feed control system. The surface quality was measured utilising SJ-201P, Mitutoyo Japan surface roughness tester. MRR is the amount of material detached by the tool in a unit time and can be calculated as weight lost divided by machining time. MRR is a vital parameter for any machining system; therefore, it should be as high as possible to minimise the overall cost of machining. For determining MRR, the initial weight and final weight of each specimen were measured three times and average values were used to calculate MRR. MRR was calculated by the formula given by Equation (1).

$$\mathrm{MRR} = \left(\frac{W_i - W_f}{t}\right) \quad (1)$$

Where 'W_i and W_f' are the original and finishing weight of the specimen, respectively, and 't' is machining time.

The levels of the control parameters, i.e. used in the experimentation, are presented in Table 1. The parameters and their ranges are decided based on the findings of the pilot experiments.

Box–Behnken design technique is utilised to conduct experiments. The experimental results are presented in Table 2.

Table 1. Levels of the control (input) parameters

Level	Spindle Speed (mm/min)	Feed Rate (mm/rev)	Depth of cut (mm)
Low	32.32	0.045	0.50
Medium	56.52	0.080	0.75
High	87.92	0.125	1.00

Table 2. Responses, Effect of input control restrictions on output, i.e. surface quality and MRR

	Control parameters			Response	
Sl. No.	Spindle Speed (m/min)	Feed Rate (mm/rev)	Depth of Cut (mm)	SR (µm)	MRR (g/sec)
1	35.33	0.045	0.75	1.70	0.04184
2	87.92	0.045	0.75	2.82	0.09972
3	35.32	0.125	0.75	6.43	0.11515
4	56.52	0.080	0.75	2.38	0.10318
5	35.33	0.080	0.50	2.26	0.05752
6	87.92	0.080	0.50	2.38	0.13712
7	35.33	0.080	1.00	2.02	0.09587
8	87.93	0.080	1.00	2.29	0.15072
9	56.53	0.045	0.50	1.76	0.05427
10	56.53	0.125	0.50	5.18	0.10132
11	56.53	0.045	1.00	1.94	0.07844
12	56.53	0.125	1.00	4.88	0.12614
13	56.52	0.125	0.75	3.85	0.14752

ANOVA and RSM analysis were conducted using MINITAB 19 software.

3.0 Results and Discussion

3.1 Surface Roughness

To evaluate the impact of control parameters on surface roughness and predict the optimal control settings, various analyses were conducted. The results obtained are presented and discussed in the following paragraphs.

3.1.1 ANOVA Results

To determine the percentage contribution of different control parameters on SR, an Analysis of Variance

Table 3. ANOVA analysis for Surface Roughness

Source	DF	AdjSS	AdjMS	F-Value	P-Value	% contribution
Spindle speed	1	0.2404	0.24042	0.48	0.538	1.87%
Feed rate	1	7.8076	7.80761	15.59	0.029	60.75%
Depth of cut	1	0.0285	0.02854	0.06	0.827	0.221%
Square	3	2.6652	0.88838	1.77	0.325	1.687%
Spindle Speed*Spindle speed	1	0.2168	0.21683	0.43	0.558	1.667%
Feed rate*Feed rate	1	2.4172	2.41721	4.83	0.116	18.87%
Depth of cut*Depth of cut	1	0.0208	0.02083	0.04	0.851	0.16%
2-Way interaction						
Spindle speed*Feed rate	1	1.5602	1.56019	3.11	0.176	12.14%
Spindle speed*Depth of cut	1	0.0038	0.00377	0.01	0.936	0.29%
Feed rate*Depth of cut	1	0.0537	0.05372	0.11	0.765	0.041%
Error	3	1.5029	0.50095			
Total	12	27.8778	12.8500			

(ANOVA) was performed, considering both individual and interaction effects. The results of the ANOVA are presented in Table 3.

The ANOVA results indicate that the feed rate is the most significant factor influencing surface roughness, followed by the interaction terms involving the feed rate. The feed rate contributes approximately 60% to the surface roughness.

3.1.2 Modelling of Surface Quality

The second-order mathematical model for surface roughness has been developed and is presented as follows:

Surface Roughness = 2.31 + 0.009 *s- 20.2*f -1.7*d + 0.000486*s*s+ 703*f*f+ 1.47*d*d - 0.954*s*f + 0.0046*s*d - 11.5*f*d (2)

The variables 's' represents spindle speed, 'f' denotes feed rate, and 'd' stands for depth of cut. To evaluate the predictability and reliability of the developed model, an analysis was conducted. The analysis revealed an F-value of 5.85, indicating that the model is significant, with only a 0.01% chance that the F-value is large due to noise. Additionally, the P-value is below 0.05, suggesting that the model's relationships are significant at a 95% confidence level. Since the feed rate has the lowest P-value (0.029) and the highest F-value, it is identified as the most influential factor. The regression analysis results, presented in Table 4, show that the predicted R^2 value of 0.7466 is reasonable, with an adjusted R^2 value of 0.8732, indicating a modification of less than 0.2. The accuracy is deemed acceptable based on the S/N ratio, with a value greater than 4 being required. Our S/N ratio of 14.054 confirms that the model provides an acceptable signal. Therefore, the relationship can be used to guide the design space.

Table 4. Summary of results for surface quality

S	R^2	R^2(adj)	R^2(pred)
0.707352	0.9220	0.8732	0.7466

The impact of main factors, including spindle speed, feed rate, and depth of cut, is illustrated in Figure 2. The fitted mean graph indicates that surface roughness is primarily affected by feed rate, with an increase in feed rate leading to higher surface roughness. Both spindle speed and depth of cut have minimal or negligible influence on surface roughness. These findings align with the results observed in the ANOVA analysis.

3.1.3 Interaction Graph of Fitted Mean for Surface Quality

The interaction plot shown in Figure 3 shows the various interactions of two factors for surface quality. As shown in the graph, the interaction between spindle speed and feed rate has a greater impact on surface quality compared

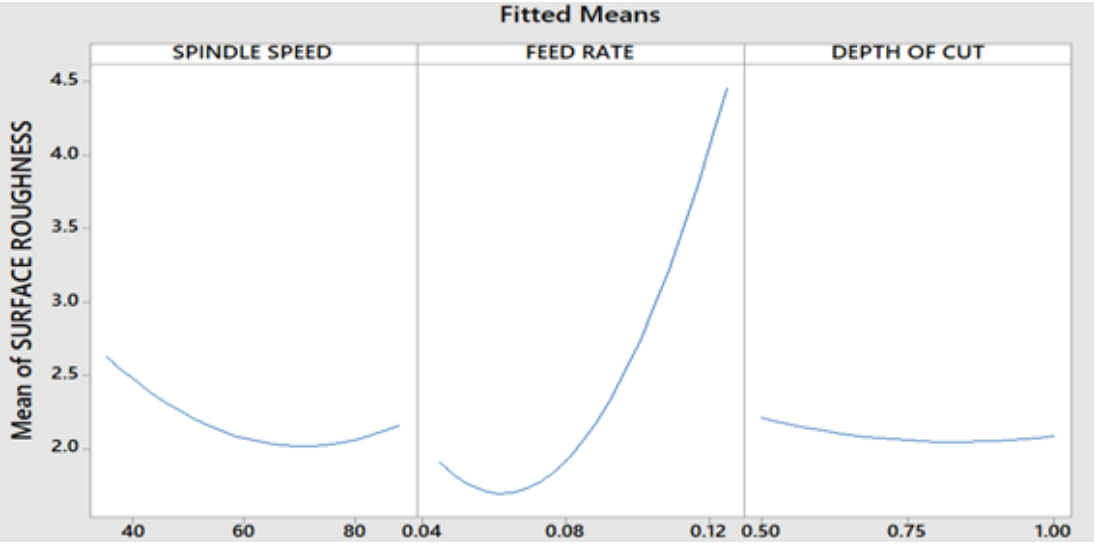


Figure 2. Mean effect plot for surface quality with input parameters.

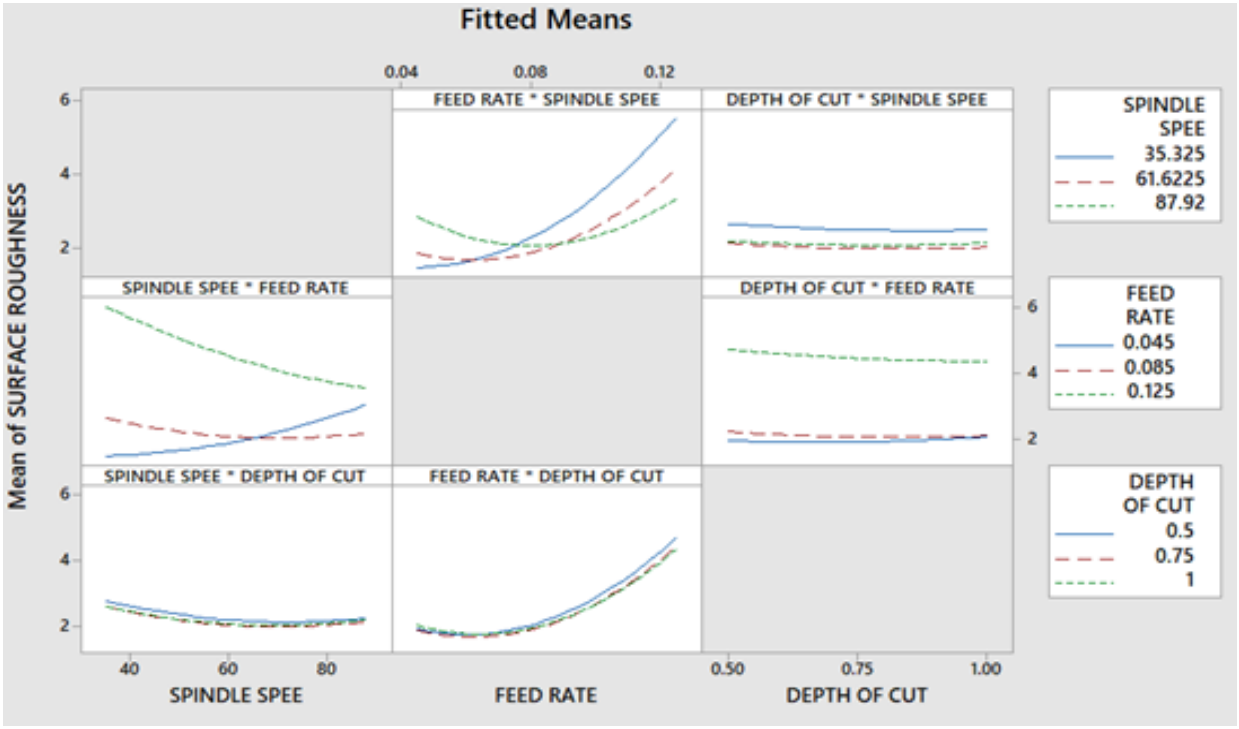


Figure 3. Interaction graph of fitted mean for surface roughness.

to other factor interactions. In contrast, the interactions between depth of cut-spindle speed and depth of cut-feed rate are less significant. The three levels of spindle speed, feed rate, and depth of cut, as depicted in the graph, represent their lower limits, mean values, and upper limits.

3.1.4 Response Surface Plot for Surface Quality

The various response surface plots for surface roughness are presented in Figure 4. In the first graph, it is observed that the maximum surface roughness corresponds to the highest feed rate and depth of cut, while the minimum surface roughness occurs at the lowest values of feed rate and depth of cut. This plot also demonstrates that feed rate has a greater influence on surface roughness than depth of cut, as the change in surface roughness along the feed rate is more significant than along the depth of cut. The second plot illustrates the interaction between spindle speed and depth of cut for surface roughness at a constant feed rate. In this plot, the minimum surface

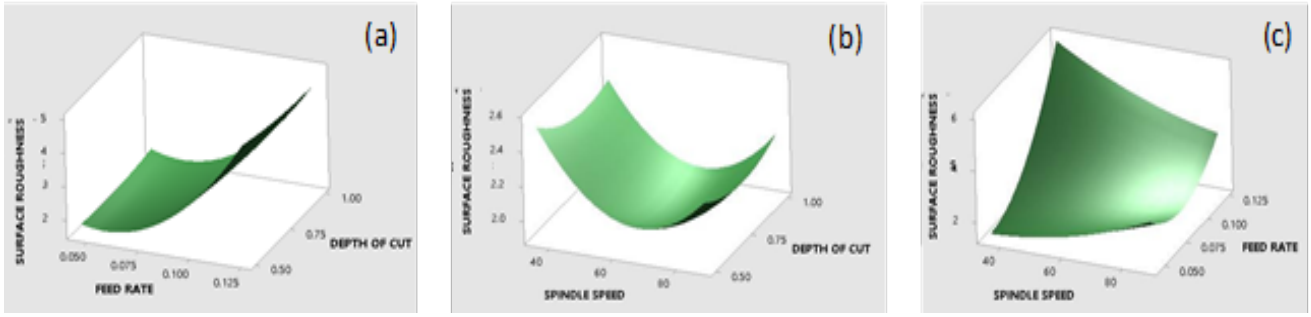


Figure 4. Response Surface Plot of **(a)** depth of cut and feed rate, **(b)** spindle speed and depth of cut, and **(c)** feed rate and spindle speed for surface roughness.

roughness is observed at a spindle speed of 60 m/min and a depth of cut of 0.75 mm. Similarly, the third plot shows the interaction between spindle speed and feed rate for surface roughness, with the minimum surface roughness occurring at the lowest values of both spindle speed and feed rate.

3.2 Material Removal Rate (MRR)

In order to find the effect of control restriction on MRR as well as to forecast the optimum control restriction for the same, different analyses were carried out, and results obtained are presented in the following paragraph.

3.2.1 Analysis of Variance (ANOVA)

To determine the percentage impact of various control restrictions on MRR, the ANOVA is conducted considering individual as well as interaction terms. The ANOVA results are given in Table 5.

The ANOVA results indicate that the feed rate is the most significant factor influencing MRR, followed by spindle speed. The feed rate contributes approximately 43.58% to MRR, while spindle speed accounts for 38.23%. Together, these two factors contribute about 82% to MRR, making them the most influential parameters. The overall error in the analysis is approximately 6%.

3.2.2 Modelling of Material Removal Rate

The second-order mathematical model for MRR has been developed and is presented below:

$$MRR = -0.231 + 0.00149 *s + 2.15*f + 0.334*d + 0.000003*s*s - 8.16*f*f - 0.154*d*d + 0.0006*s*f - 0.00091*s*d + 0.004*f*d \quad (3)$$

Where 's', 'f', and 'd' are defined in the same manner as in Equation 2. The predictability and adequacy of the developed model were evaluated through analysis. The results show an F-value of 6.75, indicating that the model is significant, with only a 0.01% chance that such a large F-value could occur due to noise. P-values below

Table 5. ANOVA analysis results for Material Removal Rate (MRR)

Source	DF	AdjSS	AdjMS	F-Value	P-Value	% Contribution
Spindle speed	1	0.004343	0.004343	18.59	0.023	38.237%
Feed rate	1	0.004944	0.004944	21.17	0.019	43.528%
Depth of cut	1	0.001129	0.001129	4.83	0.115	9.94%
Square	3	0.000637	0.000212	0.91	0.530	
Spindle speed*spindle speed	1	0.000007	0.000007	0.03	0.877	0.06%
Feed rate*feed rate	1	0.000326	0.000326	1.40	0.323	2.077%
Depth of cut*depth of cut	1	0.000228	0.000228	0.97	0.396	2.007%
2-way interaction						
Spindle speed *feed rate	1	0.000001	0.000001	0.00	0.961	0.01%
Spindle speed*depth of cut	1	0.000147	0.000147	0.63	0.486	1.294%
Feed rate*depth of cut	1	0.000000	0.000000	0.00	0.996	0%
Error	3	0.000701	0.000234			6.17%
Total	12	0.014888				

0.05 suggest that the model terms are significant. In this case, spindle speed and feed rate are significant terms in the model. Values greater than 0.1000 indicate that those terms are not significant. The regression analysis of the developed model (shown in Table 6) reveals that the Predicted R^2 of 0.7577 is in reasonable agreement with the Adjusted R^2 of 0.8117, with a difference of less than 0.2. Adequacy is measured by a ratio greater than 4, which is desirable. Therefore, this model can be effectively used to guide the design space.

Table 6. Model Summary for MRR

S	R^2	R^2(Adj)	R^2(Pred)
0.0152842	95.29%	81.17%	75.77%

3.2.3 Mean Effect Plots for MRR

The impact of main factors on MRR and their interactions is depicted in Figure 5. Based on the fitted mean graph, MRR is primarily influenced by feed rate, followed by spindle speed, while depth of cut has the least effect on material removal rate. These findings are consistent with the results observed in the ANOVA analysis of MRR.

3.2.4 Response Surface Plot for MRR

To assess the effect of process parameters on MRR, response plots were created and are shown in Figure 6. The first plot illustrates the interaction between feed rate and depth of cut for MRR, with feed rate held constant.

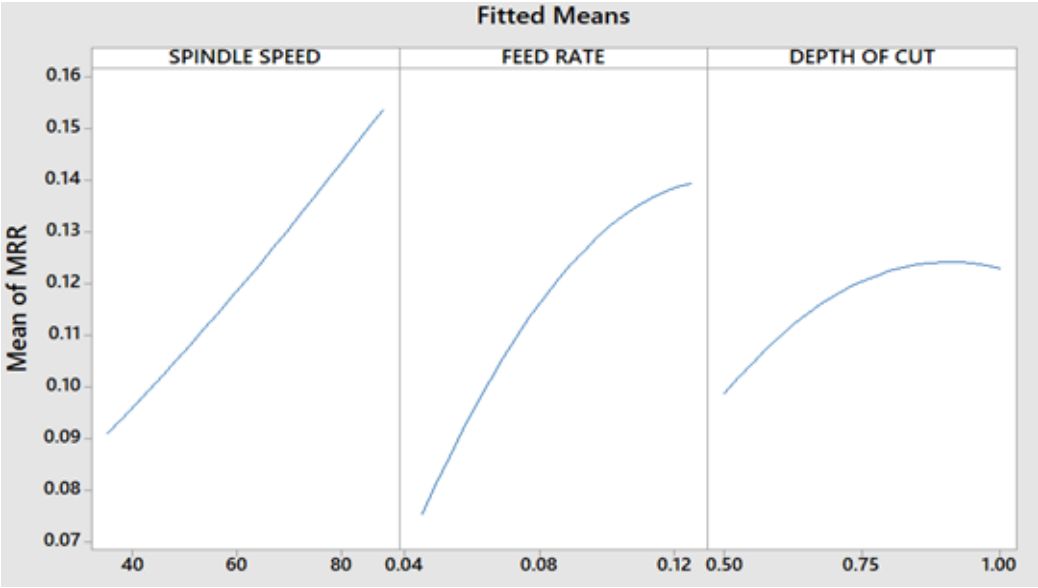


Figure 5. Mean effect plot for MRR.

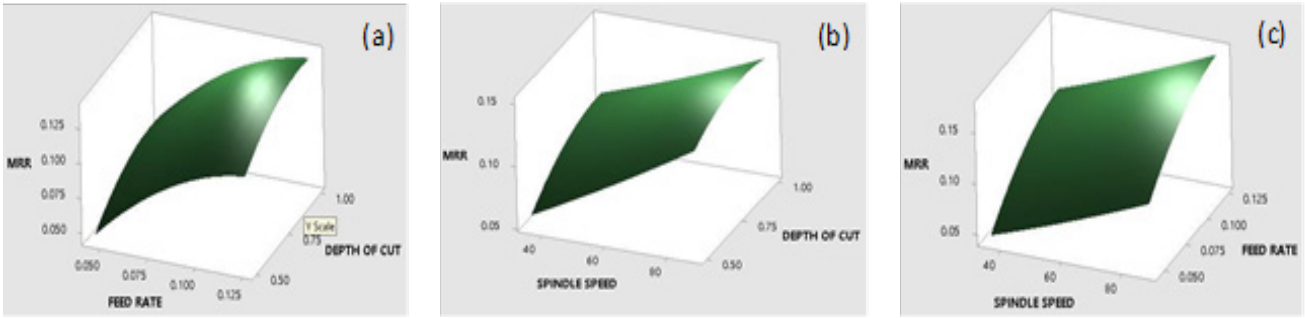


Figure 6. Response Surface Plots of **(a)** depth of cut and feed rate, **(b)** spindle speed and depth of cut, and **(c)** feed rate and spindle speed for MRR.

The graph indicates that the maximum MRR occurs at the highest values of both feed rate and depth of cut, meaning that increasing the process parameters leads to an increase in MRR. The second plot demonstrates the interaction between spindle speed and depth of cut for MRR, again with a constant feed rate. In this plot, the maximum MRR is observed at the highest values of both spindle speed and depth of cut. Similarly, the third plot shows the interaction between spindle speed and feed rate for MRR, where the maximum MRR occurs at the highest values of both spindle speed and feed rate.

4.0 Optimisation

To determine the optimal values for surface roughness and MRR, optimisation was performed using Response Surface Methodology (RSM). The optimisation results are presented in Figure 7. The criteria used for the optimisation analysis are provided in Table 7.

The optimization plot presented in Figure 7 clearly shows that the optimal settings for the input parameters (spindle speed, feed rate, and depth of cut) to achieve the maximum values for the responses (surface roughness

Table 7. Optimisation criteria

Response	Goal	Lower limit	Target	Upper limit
MRR	Maximum	0.0.04184	0.15072	0.15072
Surface Roughness	Minimum	1.7	1.70000	6.43

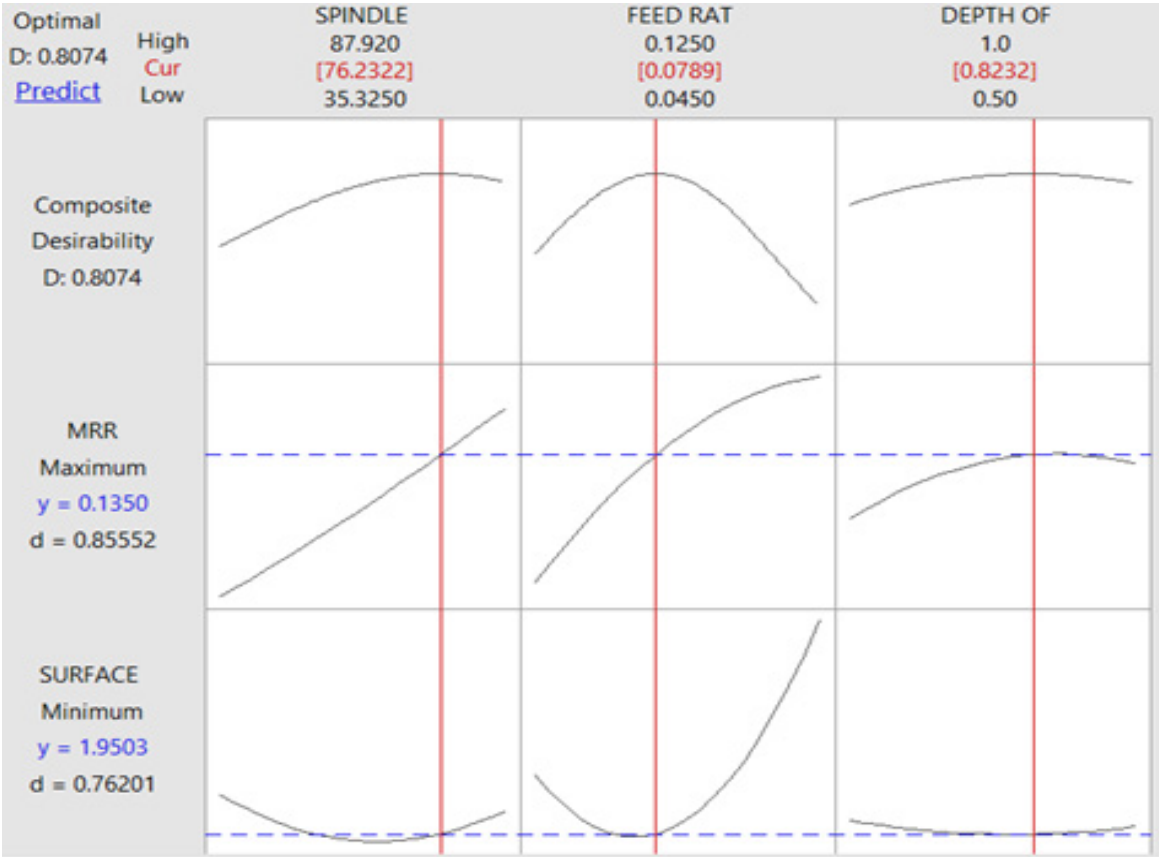


Figure 7. Optimisation plot for MRR and surface roughness.

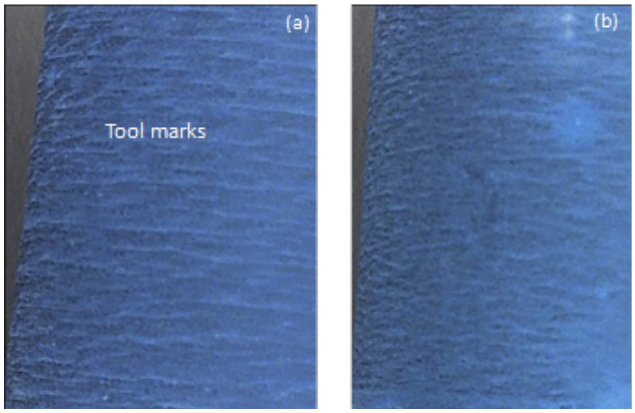


Figure 8. Machined surface at 8X magnification **(a)** Maximum MRR (experiment 3) and **(b)** Minimum SR (experiment 1).

and material removal rate) are a spindle speed of 76.23 m/min, a feed rate of 0.079 mm/rev, and a depth of cut of 0.80 mm. The predicted optimum values for material removal rate and surface roughness are 0.135 g/sec and 1.95 micrometres, respectively.

From the images of Figure 8 (a), we can observe that on increasing the MRR, the surface has deep tool marks, and some tool chatter marks are visible. Higher feed rate, with low spindle speed, are the main reasons for deep tool marks.

5.0 Conclusions

The experimental investigation conducted in this study successfully optimised the machining process parameters for E-Glass/Jute fibre composites using Response Surface Methodology (RSM) for electric vehicle applications. The study identified the optimal combination of spindle speed, feed rate, and depth of cut, which resulted in the best values for material removal rate (MRR) and surface roughness. Specifically, a spindle speed of 76.23 m/min, feed rate of 0.079 mm/rev, and depth of cut of 0.80 mm yielded an optimum MRR of 0.135 g/sec and surface roughness of 1.95 micrometres. Among the process parameters, feed rate was found to be the most influential factor, contributing significantly to both surface roughness and MRR. Although the feed rate had a dominant effect on surface roughness (60%) and MRR (43%), spindle speed was the second most influential parameter, particularly for MRR, contributing 38% to its variation.

Depth of cut had minimal impact on both surface roughness and MRR, and no significant effect was found when combined with spindle speed. The study also highlighted the importance of parameter interactions, where the interaction between feed rate and depth of cut significantly affected MRR, while the interactions between feed rate and spindle speed, as well as feed rate with itself, had a significant influence on surface roughness. The use of 3D surface contour plots was invaluable in visualising these relationships and determining the optimum process parameters. Overall, this research provides crucial insights into the machining of fibre-reinforced composites, offering valuable guidelines for enhancing the machining efficiency of materials used in lightweight and high-strength structural components for electric vehicles.

6.0 References

1. Verma V, Sayyed AHM, Sharma C, Shukla DK. Tensile and fracture properties of epoxy alumina composite: role of particle size and morphology. J Polym Res. 2020; 27(12):1–14. https://doi.org/10.1007/s10965-020-02359-z
2. Singh Y, Singh J, Sharma S, Sharma A, Singh Chohan J. Process parameter optimisation in laser cutting of Coir fibre reinforced Epoxy composite – A review. Mater Today Proc. 2021; 48:1021–7. https://doi.org/10.1016/j.matpr.2021.06.344
3. Abhishek K, Datta S, Chatterjee S, Mahapatra SS. Parametric optimisation in turning of CFRP (epoxy) composites: A case experimental research with exploration of HS algorithm. Appl Mech Mater. 2014; 619:54–7. https://doi.org/10.4028/www.scientific.net/AMM.619.54
4. Ali H, Rohit K, Dixit S. Fabrication and characterisation of eco-friendly natural human hair fibre reinforced polyester composite. J Nat Fibers. 2023; 20(1). https://doi.org/10.1080/15440478.2023.2181268
5. Nagavally RR. Composite materials - History, types, fabrication techniques, advantages, and applications. Proc 29th IRF Int Conf. 2016; 2:25–30.
6. Rajendran A, Paul B, Shunmugesh K. Optimisation of milling parameters in jute fibre reinforced epoxy

composite using GRA. Mater Today Proc. 2020; 43:3951–5. https://doi.org/10.1016/j.matpr.2021.02.663
7. Kumar S, Gupta M, Satsangi P, Sardana H. Modelling and analysis for surface roughness and material removal rate in machining of UD-GFRP using PCD tool. Int J Eng Sci Technol. 1970; 3(8):248–70. https://doi.org/10.4314/ijest.v3i8.20
8. Singh NK, Pradhan SK. Experimental and numerical investigations of pipe orbital welding process. Mater Today Proc. 2019; 27:2964–9. https://doi.org/10.1016/j.matpr.2020.04.902
9. Singh NK, Sethuraman B, Gupta M. Analysis and optimisation of laser beam welding parameters for aluminium composite (Al-Zn-Cu alloy) by Grey relational optimisation. Micro. 2024; 4(4):641–58. https://doi.org/10.3390/micro4040039
10. Singh NK, Balaguru S, Rathore RK, Namdeo AK, Kaimkuriya A. Multi-criteria decision-making technique for optimal material selection of AA7075/SiC composite foam using COPRAS technique. J Mines Met Fuels. 2023; 71(10):1374–9. https://doi.org/10.18311/jmmf/2023/34005
11. Lee HP, Ng BMP, Rammohan AV, Tran LQN. An investigation of the sound absorption properties of flax/epoxy composites compared with glass/epoxy composites. J Nat Fibers. 2017; 14(1):71–7. https://doi.org/10.1080/15440478.2016.1146643
12. Chauhan S, Sahu S, Ansari MZ. Effect of boundary support conditions on impact behaviour of silicone pin-reinforced polymer sandwich composite structure. Polym Compos. 2020; 41(12):5104–15. https://doi.org/10.1002/pc.25778
13. Krishna R, Gupta PK. Optimising pressure drop in 90° bend horizontal pipelines for dense slurry flow: A response surface methodology approach. Proc Inst Mech Eng Part E J Process Mech Eng. 2024. https://doi.org/10.1177/09544089241271765
14. Rana RS, Nigrawal A, Rana S, Purohit R. Design and development of epoxy hybrid composite gears for low-powered application. Adv Mater Process Technol. 2020; 6(2):380–9. https://doi.org/10.1080/2374068X.2020.1731154
15. Singh NK, Rathore RK, Sinha AK, Narayan H. Multi-objective optimisation of process parameters subjected to end milling process of AA7075 alloy through TOPSIS method. AIP Conf Proc. 2024; 3111(1). https://doi.org/10.1063/5.0221440