

## Research Article

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# Estimating of cutting force and surface roughness in turning of GFRP composites with different orientation angles using artificial neural network

<https://doi.org/10.1515/rams-2022-0286>

received May 25, 2022; accepted November 10, 2022

**Abstract:** Glass fiber-reinforced polymer (GFRP) composite materials are widely used in many manufacturing industries due to their low density and high strength properties, and consequently, the need for precision machining of such composites has significantly increased. Since composite materials have an anisotropic and heterogeneous structure, the machinability of composite materials is quite different from conventional materials. In the machining of GFRP composite pipes, tool wear, cracks or delamination, a rough surface, etc., many unwanted problems may occur. Therefore, GFRP composite pipes are difficult to process. To prevent such problems, it is very crucial to select suitable process parameters, thereby achieving the maximum performance for the desired dimensional integrity. In this study, through turning of GFRP composites with different orientation angles ( $30^\circ$ ,  $60^\circ$ , and  $90^\circ$ ), the effects of cutting speed (50, 100, and  $150 \text{ m}\cdot\text{min}^{-1}$ ), feed rate (0.1, 0.2, and  $0.3 \text{ mm}\cdot\text{rev}^{-1}$ ), and depth of cut (1, 2, and 3 mm) on cutting force and surface roughness were determined. Then, with the use of these machining parameters, a model of the system for determining cutting force and surface roughness was established with artificial neural networks (ANNs). The ANN was trained using Levenberg–Marquardt backpropagation algorithm. It has been observed that the results obtained with the ANN model are very close to the data found in experimental studies. In both experimental and model-based analysis, minimum cutting force (44 N) and surface roughness ( $2.22 \mu\text{m}$ ) were achieved at low fiber orientation angle ( $30^\circ$ ), low feed rate ( $0.1 \text{ mm}\cdot\text{rev}^{-1}$ ), and depth of cut (1 mm) at high cutting speeds ( $150 \text{ m}\cdot\text{min}^{-1}$ ).

**Keywords:** GFRP, fiber orientation, machining, surface roughness, cutting force, artificial neural network

## 1 Introduction

In this modern time, most of multi parameter processes can be modeled via artificial neural networks (ANNs) by which almost real-time monitoring of variety of experimental process becomes possible. With such models, besides the real-time monitoring, one can estimate the optimum input parameters for the desired outcome of experiments without conducting the physical time consuming and costly experiments. Similar to the ANN models developed for applied science found in the literature, identifying optimum input parameters for a desirable output in machining and turning processes is also possible with appropriate ANN models. In particular, it is thought that such models are important in estimating the optimum parameters needed in glass fiber-reinforced polymer (GFRP) processing systems. GFRP materials are the ones introduced and used in variety of high-tech areas in this contemporary time.

Naturally, the matter utilized in high-tech areas, such as defense, aviation, space, maritime, bioengineering and transportation industry, and electrical and electronics [1–3], need to possess exclusive properties, such as low density, rigidity, high strength, fatigue resistance, abrasion and impact resistant and resistant to corrosion [4,5]. In some applications, often combination of these properties (which is highly difficult) may be desired. Composite materials are structured by combining at least two of different materials at a macro level (insoluble in each other). Fiber-reinforced layered composites are of these materials structured with fiber layers that could differ in type and orientation. The arrangement of the fibers in the matrix enables the composite material to show an anisotropic and somehow inhomogeneous structure, which is important factor affecting the mechanical properties and machinability of composite materials [1,4–6]. Such structural properties beget significant differences between machining of composite materials and of conventional metals, where plastic deformation dominates the material removal process.

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The composite materials, such as fiber-reinforced polymer (FRP) and GFRP composites, have a much more complex structure (mainly near to the net shape to ensure geometric tolerance, needed for surface quality), which requires a different chip removal mechanism [7]. To achieve a qualitative cutting performance in machining of GFRP composites, it is necessary to select appropriate cutting parameters in regard to this complex metal removal mechanism [8,9]. The appropriate cutting parameters provide significant saving in both financial and time costs and consequently increase in process efficiency [10].

Besides the production method [11–15], tool material [7,16,17], tool geometry [18–21], machining parameters [22–25], and fiber orientation [18,26–29] are important in machining of GFRP composites. With both experimental and mathematical models, it has been made clear that chip formation and defects are highly correlated with fiber orientation in the machining of FRP and GFRP composites [30]. Kini and Chincholkar [22] experimentally investigated the effects of machining parameters on surface roughness and material removal rate in  $\pm 30^\circ$  filament wound GFRP processing using a coated tungsten carbide cutting tool. The obtained results showed that surface roughness is primarily influenced by the feed rate and depth of cut. Therefore, to achieve a better surface quality, it is important to analyze various machining conditions to select the ones best suited to process optimization [31]. Palanikumar [32] showed that mathematical models (they developed) can be effectively used to estimate surface roughness in turning GFRP workpieces based on machining parameters (fiber orientation, cutting speed, feed rate, depth of cut). He concluded that the surface roughness decreased as the cutting speed and depth of cut increased and the surface roughness increased as the fiber orientation angle and feed rate increased. Khashaba et al. developed regression models by which multivariate regression analysis was conducted and correlations between processing parameters and the responses were investigated in drilling of GFRP [33,34]. They found that the thrust force was the most effective factor in drilling GFRP, and the laminate thickness was highly effective in the measured temperature. Neeli et al. used gray relational analysis (GRA) and desirability function analysis to optimize machining parameters, such as fiber orientation angle, helix angle, spindle speed, and feed rate for milling GFRP composites [35]. They showed that fiber orientation angle is the most important parameter for GFRP composites before helix angle, feed rate, and spindle speed.

To enable a wide-range surface roughness analysis in machining, particular mathematical models have been

developed and analysis of variance (ANOVA) was performed with 95% confidence level to validate these models with respect to experimental studies [36]. Ekici and Motorcu investigated the effects of drilling parameters and tool coating conditions on the processing of CFRP composites and optimized with the help of Taguchi-based GRA. ANOVA showed a high correlation coefficients between  $R_a$ ,  $D_f$ , and UCFF, and also drilling parameters as well as hole characteristics [37]. They used ANOVA to determine the effects of control factors on the hole damage, which occurs in the form of delamination of the cutting tool geometry in drilling GLARE. They concluded that feed rate and cutting speed were more effective than cutting tool geometry on delamination formation [38]. It was also reported that there was very little wear in the cutting tools used in their study under different drilling conditions [6].

To develop robust and wide-range parameter optimization machining methods, recently, ANN-based models have been introduced to virtually process FRP composites [39] and are reported as more precise in forecasting system's outcome. In general, Levenberg–Marquardt (LM) backpropagation learning algorithm is used in the learning phase of the ANN model. In the processes like FRP machining, some input parameters, such as cutting force, machining or turning angle tool parameters, are considered input parameters, while outcomes such as surface roughness are used for supervising the model to learn. In this concept, Jenarathanan et al. also developed an ANN model for artificially estimating the optimum cutting forces for GFRP processing at different fiber orientations and cutting parameters. The cutting force estimated by this model was found to be in line with the results of experimental models [40]. In parallel to the studies devoted to estimate the system outcome, some studies concentrated on the performance optimization of the model using different learning algorithms. Ghosh et al. [41] compared LM and gradient descent methods to train the ANN they used in their study. They stated that the network trained with the LM algorithm gave better results. With the same goal, Mishra and Singh [42] analyzed the neural network which used to develop the prediction model of tool chatter severity with resilient propagation, conjugate gradient-based, quasi-Newton-based, and LM algorithms. They found that LM algorithm predicts chatter with a lower deviation than other training algorithms, and therefore, they suggested the LM algorithm to prefer. From the above information, it can be concluded that optimization of all parameters involving in a machining process can easily be achieved with ANN-based models trained with appropriate data [10].

In reality, excessive cutting forces cause various damages to the material. The damaged material cannot be accepted in the production cycle. The most critical damages are short tool life, thermal overload of polymeric material, chatter marks, delamination, fiber fracture, fiber pull-out, burning, and formation of powder-like chips as described in refs [18,43–45]. It has been observed that in the processing of GFRP composites, these damages are mainly due to the fiber orientation, while tool geometry and machining parameters have a secondary effect [18,26]. However, a general standard conclusion in this direction has not been reached yet, and it is understood that more research is needed to have effective control of this issue and to go beyond the uncertainty.

In this particular study, first, the effects of different fiber orientation angles (30, 60, and 90°) and different machining parameters, such as feed rate, cutting speed and depth of cut, on the cutting force and surface roughness values were investigated in the turning of GFRP composites. Then, using these machining parameters, an ANN was developed for multi-criteria optimization involving cutting force and surface roughness. The ANN was trained with the experimentally obtained data using LM backpropagation algorithm and then tested. The test results showed that the developed ANN model well simulates the experimental studies. Therefore, we think that this model will contribute to the studies investigating the relationship between the surface roughness and cutting force at different fiber orientations.

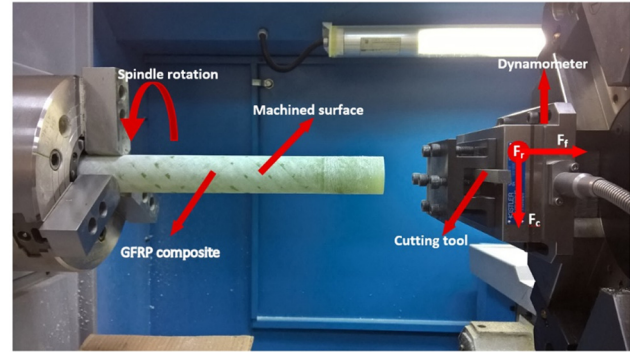
## 2 Materials and methods

In the experimental part of the study, GFRP pipes, which are recommended to be used where high strength and electrical insulation are required, were used. They were manufactured by “Izoreel Composites” company, Turkey, certifying international standards (G10-FW/HGW 2375). The pipes were 500 mm long and inner/outer diameters of 44/50 mm. They were produced by means of filament winding process as impregnating glass filaments with roving and epoxy resin. The orientation of the fibers on the workpiece was adjusted during the manufacture of the pipes. The roving were wound at an angle in the 30, 60, and 90°, epoxy resin is applied and cured at 120–140°C for 3 h. The mechanical properties of GFRP are given in Table 1.

The experimental setup for turning used in this study is shown in Figure 1. The setup was comprising a SMARC brand CAK6166B X 2000 CNC lathe with a main motor

**Table 1:** Mechanical properties of GFRP

Property	Value
Young’s modulus (GPa)	20
Tensile strength (MPa)	300
Flexural strength (MPa)	350



**Figure 1:** Experimental setup.

power of 11 kW and a maximum spindle speed of 1620 rev·min<sup>-1</sup>. The maximum turning length of the turning center was 2,000 mm and the maximum turning diameter was 660 mm. All experiments were repeated two times.

Dry condition turning experiments have been conducted on GFRP composite materials of tungsten carbide (WC) cutting tool TiAlN coated by using the PVD method, triangular YBG205 grade, TNMG 160404 EF insert cutting tool, S16M-PTFNR11 tool holder of ZCC CT company. The cutting parameters used in the experiments are indicated in Table 2. The cutting parameters were designated by means of the information obtained from cutting tools manufacturers and literature [22–25,27,28].

A three-component Kistler type 9257B (Kistler Instruments AG, Winterthur, Switzerland) dynamometer was used to measure cutting force while performing the experiments, as shown in Figures 1 and 2. Kistler type 5070-A multi-channel amplifier was used to transfer the signals taken from the dynamometer in all cutting directions to the data acquisition card and linked to the computer. Then, Kistler

**Table 2:** Cutting parameters used for experiments

Cutting parameters	Value
Cutting speed (m·min <sup>-1</sup> )	50, 100, and 150
Feed rate (mm·rev <sup>-1</sup> )	0.1, 0.2, and 0.3
Depth of cut (mm)	1, 2, and 3
Fiber orientation (°)	30, 60, and 90°
Cutting tool	WC, TiAlN coated



Figure 2: Cutting force measuring setup.

Dynoware (V2.6.3.12) software was used to analyze and evaluate the collected data. The cutting force signals (all directions) were captured and filtered through a low-pass filter (10 Hz cutoff frequency). The filtered force graph taken from the DynoWare software is shown in Figure 3. Cutting force measurements were made in three directions as feed force ( $F_f$ ), radial force ( $F_r$ ), and cutting force ( $F_c$ ). The resultant cutting force  $F$  was found as  $F = (F_f^2 + F_r^2 + F_c^2)^{1/2}$  and used in the graphics.

The data plotted in Figure 3 are measured for the case GFRP 30° fiber orientation, 50 m·min<sup>-1</sup> cutting speed, 0.1, 0.2 and 0.3 mm·rev<sup>-1</sup> feed rate, and 3 mm depth of cut. While turning GFRP composites at different processing parameters, the surface roughness value ( $R_a$ ) of the machined surfaces was measured with the Time-TR-110 tester. Surface roughness measurements were carried out in accordance with ISO 4288 requirements. The measuring parameters were  $R_a$  and  $R_z$ , with a travel length of 6 mm. The cutoff length was determined as 2.5 mm. The range for roughness parameters ( $R_a$ ) were set as 0.05–15.0 μm. After the turning experiments were completed, the roughness of the machined surfaces was measured over the average of the roughness values measured at five different points.

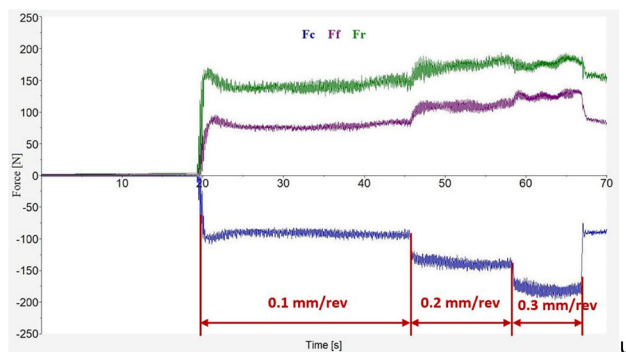


Figure 3:  $F_c$ ,  $F_f$ , and  $F_r$  force diagrams in turning of GFRP composite.

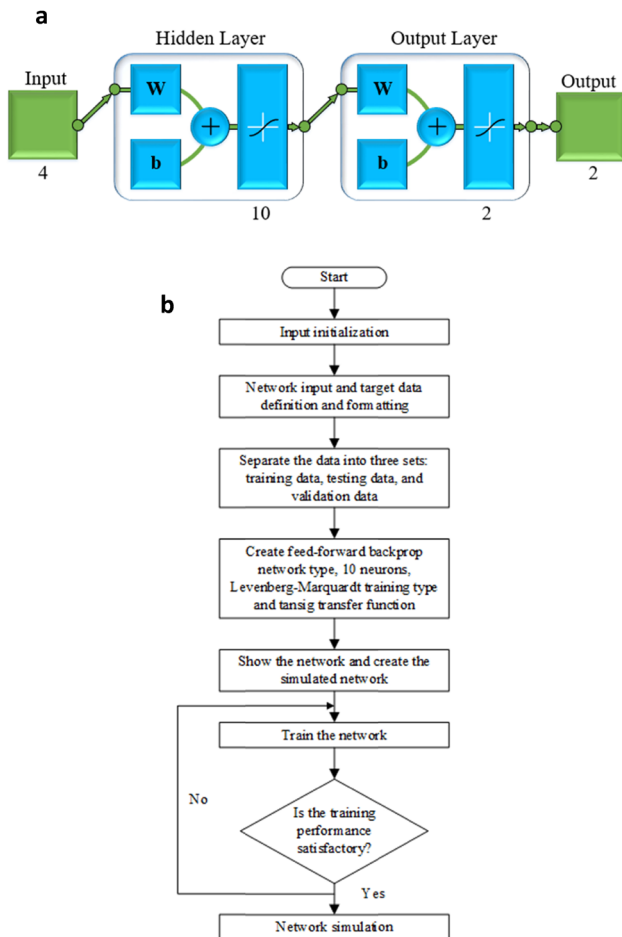
### 3 Modeling the process with ANNs

To develop a dedicated soft system for simulating machining process of turning GFRP composites with different orientation angles, and different machining parameters, a particular ANN was designed using MATLAB software, as given in Figure 4a. The flowchart followed in the design of neural network aspired to determine the most appropriate cutting forces for the targeted minimum surface roughness is shown in Figure 4b. This ANN model was specifically designed for identifying cutting force and surface roughness in regard to cutting speed, feed rate, and depth of cut machining parameters. The model was trained with 80% of the data obtained from 81 experiments and tested for the remaining 20% of the data. The ANN was feed forward type with one input layer (4 neurons corresponding machining parameters) one hidden layer (10 neurons) and an output layer with two outputs one for cutting force and the other for surface roughness. As in the literature [41,42], the LM learning algorithm was preferred because of the speed and stability it provides in the training of ANN. The neurons were activated with tansig so-called hyperbolic activation function. The network was trained with machining parameters used in the experiments until the mean square error reached the lowest possible rate for each trial. The success rate for all cases was above 90%. With the use of this model variety of experiments can be conducted virtually.

### 4 Results and discussion

The results obtained from experimental part of the study demonstrated the correlation between cutting force and machining parameters. It was observed that fiber orientation angle highly effects cutting forces (Figures 5–7) mainly due to the increase in the compression stresses,

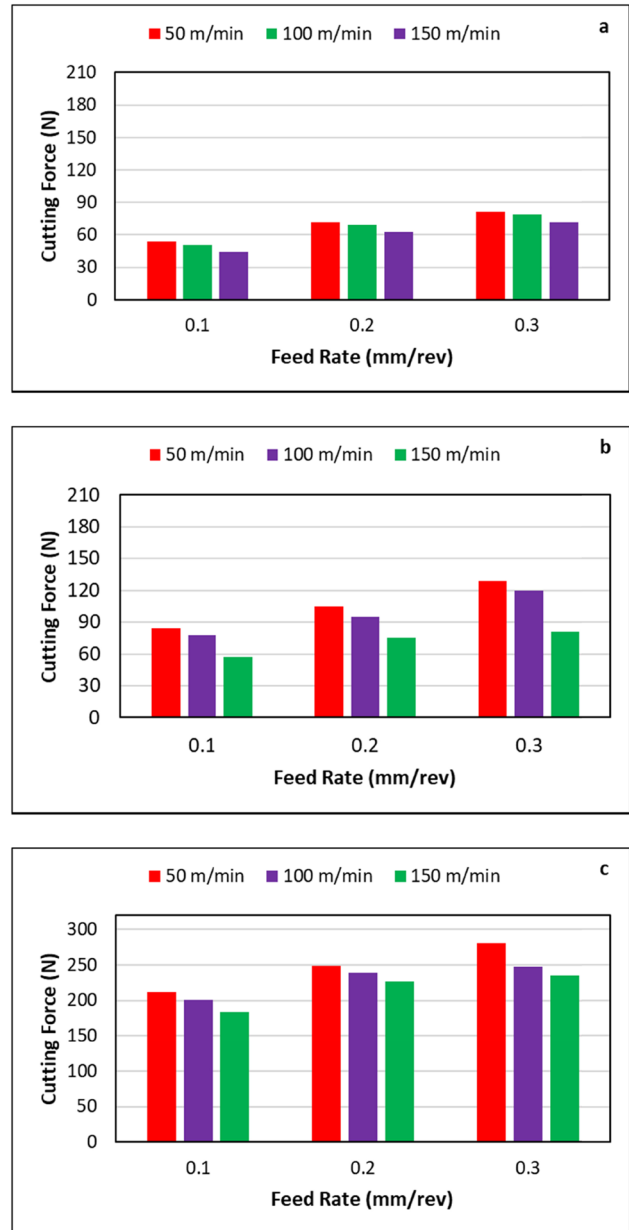




**Figure 4:** (a) ANN model. (b) Flowchart of neural network algorithm for determining cutting force and surface roughness.

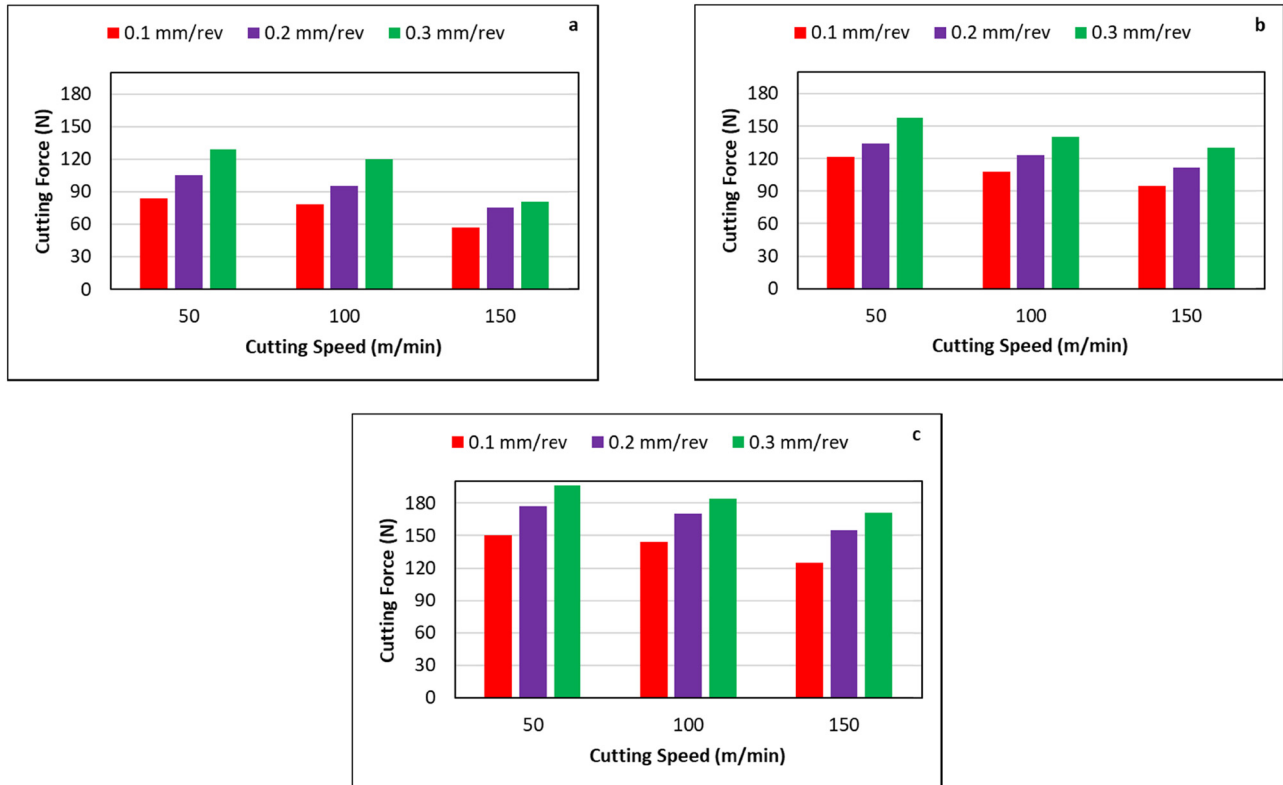
which increases as the fiber's orientation angle increases. The effects of feed rate on cutting force in turning GFRP composite at  $30^\circ$  fiber orientation angles and 1, 2, and 3 mm depths of cut are presented in Figure 5, while the effects of cutting speed and feed rate on cutting force at  $30^\circ$ ,  $60^\circ$ , and  $90^\circ$  fiber orientation angles at 2 mm depth of cut are shown in Figures 6 and 7, respectively. In the process of machining GFRP composite pipe lower cutting forces (between 44 and 81 N) were observed with a  $30^\circ$  fiber orientation angle (Figure 5a) compared to those obtained at higher fiber orientation angles (Figures 6 and 7). This confirms the advantage of machining composite materials at low orientation angles [30,32]. At  $30^\circ$  fiber orientation angle, cutting forces were also varied in accordance with the feed rate as shown in Figure 5.

The change in cutting forces with cutting speed is shown in Figure 6. As seen cutting forces decrease with the increase in cutting speed. The increase in cutting speed increases the temperature of the cutting zone.

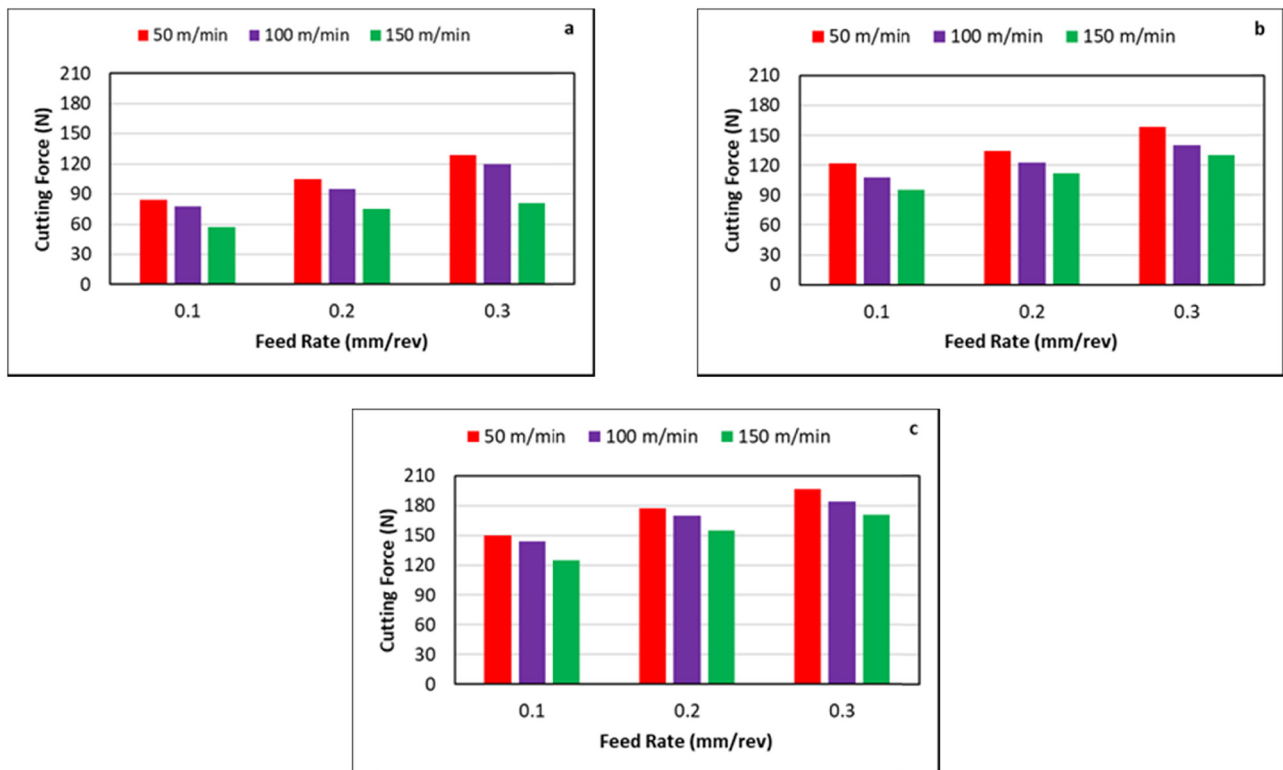


**Figure 5:** Influence of feed rate on cutting force at  $30^\circ$  fiber orientation: (a) depth of cut 1 mm, (b) depth of cut 2 mm, and (c) depth of cut 3 mm.

Increased temperature of the cutting zone causes softening of the matrix phase, resulting in lower cutting forces [46,47,48]. This result is in line with the data found in the literature [13,16,47,48]. Generally, in the processing of metals, high cutting speed is desirable for the high rate of production, but this increases tool wear [25]. The cutting force was also found as increasing with the increase of the feed rate (Figures 5 and 7), mainly due to the increase in the area of contact between the workpiece and cutting tool [1].



**Figure 6:** Influence of cutting speed on cutting force at constant depth of cut 2 mm: (a) fiber orientation 30°, (b) fiber orientation 60°, and (c) fiber orientation 90°.



**Figure 7:** Influence of feed rate on cutting force at constant depth of cut 2 mm: (a) fiber orientation 30°, (b) fiber orientation 60°, and (c) fiber orientation 90°.

It is mentioned that about a quarter (approximately 23%; 119 EJ) of the total energy losses in the world is due to tribological systematics [49]. Improving the surface quality of the materials reduces friction and wear damage and hence energy loss, which is important for sustainable energy and economy of the future [50], on the one hand, and increases the strength of materials, on the other hand. In the machining of metals, the cutting speed is more effective than the feed rate [20,22,29,51] on the surface roughness.

Among these parameters, the depth of cut had a minimum effect compared to other machining parameters. Also, cutting force increased with the increase of depth of cut, which can be observed in Figure 5.

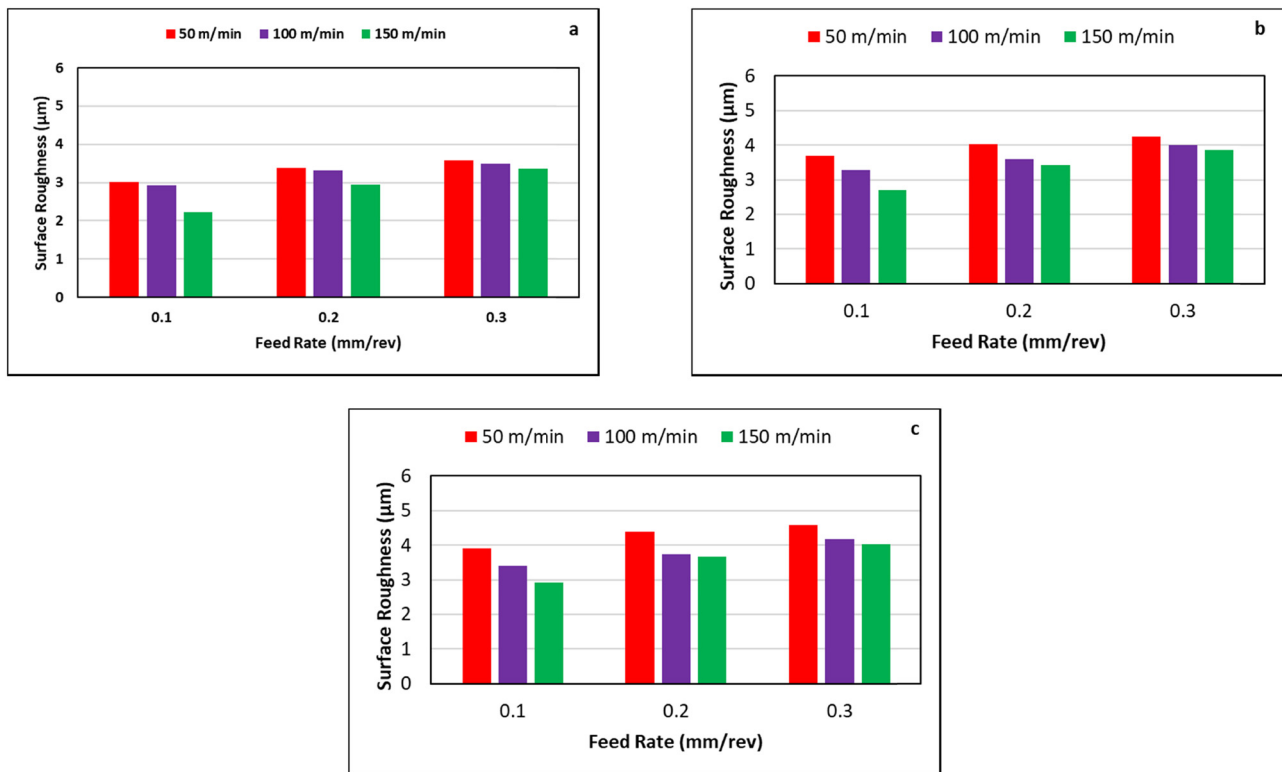
The effects of cutting parameters on surface roughness when machining carried out at 30, 60, and 90° fiber orientation angles were studied, and the results are represented in Figures 8–10. It was observed that parameters affecting surface roughness, from the most to the least, are fiber orientation, feed rate, cutting speed and depth of cut, which is in line with the literature [40].

As seen from Figure 8, at 30° fiber orientation angle, low surface roughness values ranging from 2.22 to 3.57  $\mu\text{m}$  were observed in GFRP composite material at a constant

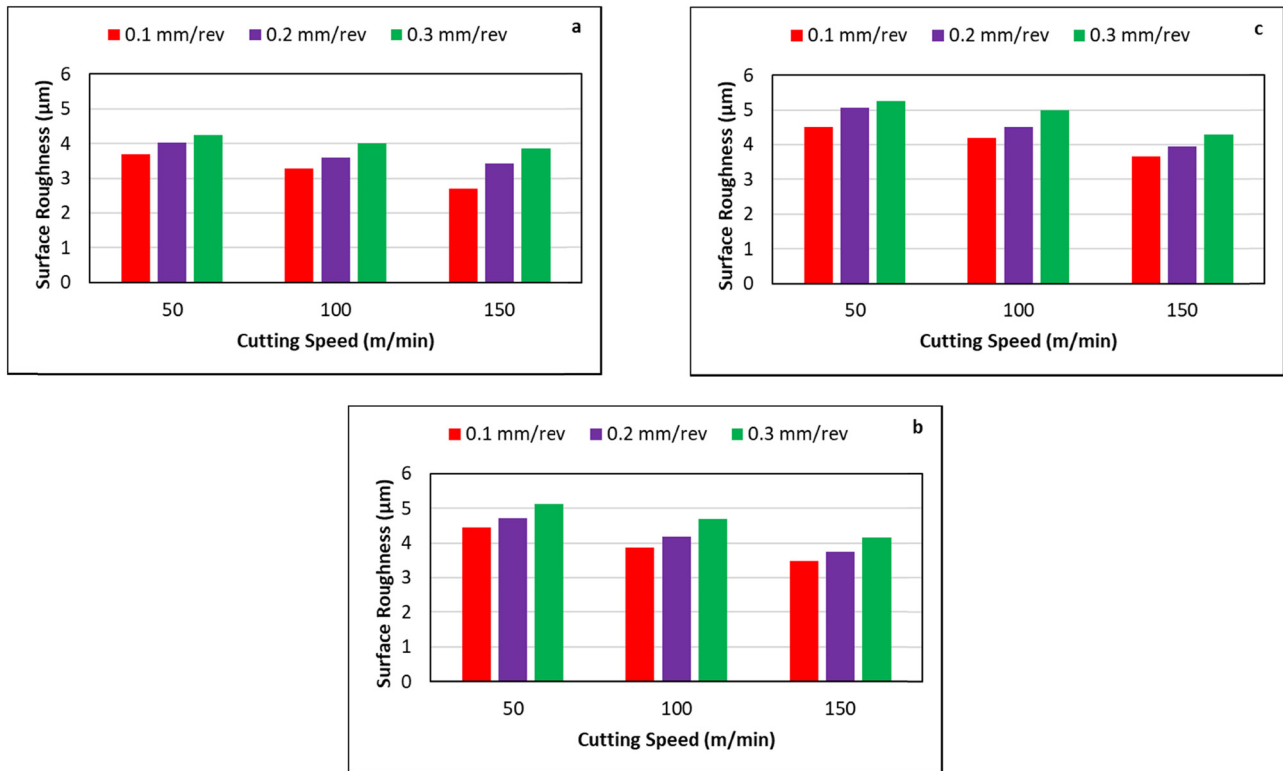
depth of cut (1 mm) and feed rates (0.1, 0.2, and 0.3 mm·rev<sup>-1</sup>). Similarly, with the same scenario, at the 60° fiber orientation angle, the surface roughness value ranged from 3.46 to 4.47  $\mu\text{m}$ , and at 90° fiber orientation angle, the surface roughness value ranged from 3.55 to 5.08  $\mu\text{m}$ . In conclusion, the larger the fiber orientation angles, the higher the surface roughness rate values are obtained, which may be explained as that, larger fiber orientation angles create a greater compression stress on the workpiece material, which increases cutting force and consequently surface roughness [1,25,26,32].

The effect of feed rate on surface roughness with fiber orientations 30, 60, and 90° is shown in Figures 8 and 10. It is seen that the surface roughness increased gradually for three different depths of cut levels with the increase of feed rates of 0.1, 1.2, and 0.3 mm·rev<sup>-1</sup>. It can be seen from the figures that the cutting force increases with increasing feed rate and consequently surface roughness increases. This is may be explained as that an increase in feed rate causes an increase in vibration because of undercut at faster traverse, and this consequently causes an increase in surface roughness [51,52].

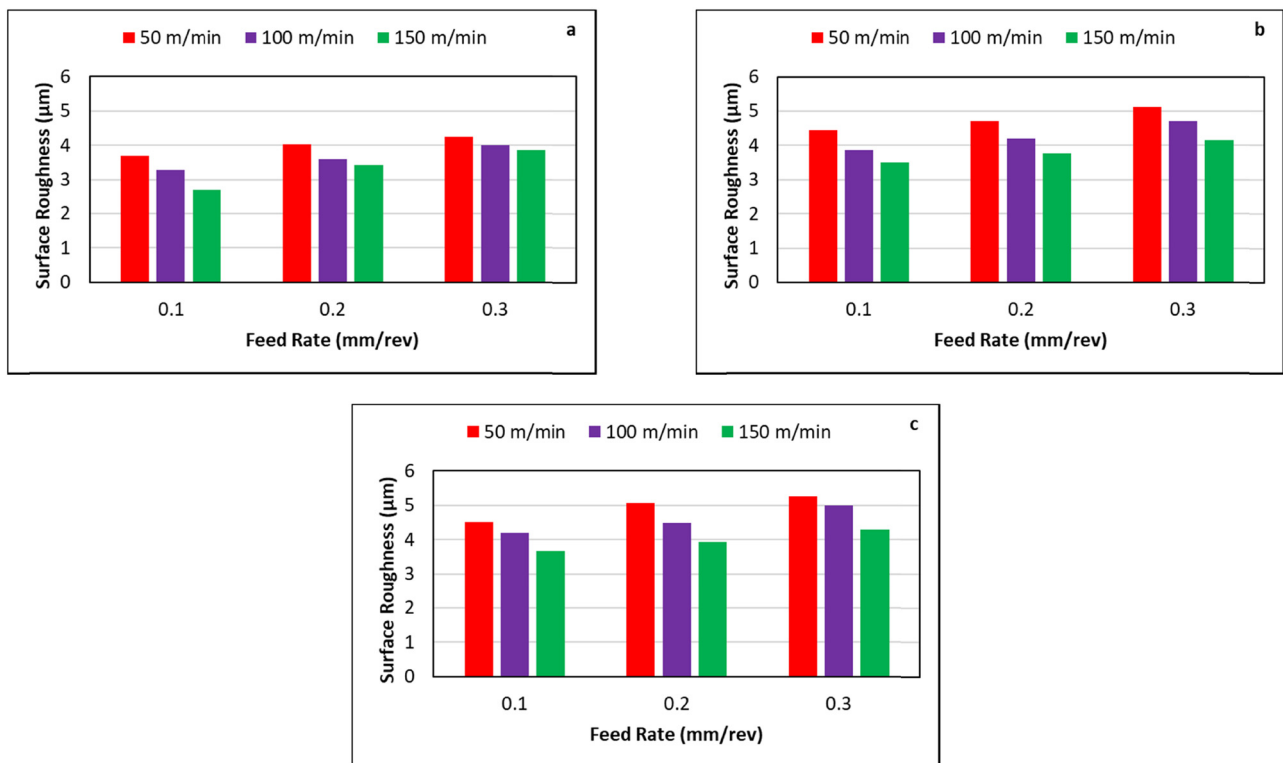
Figure 9 shows the variation in surface roughness with cutting speed at different feed rates. As seen, the



**Figure 8:** Influence of feed rate on surface roughness at 30° fiber orientation: (a) depth of cut 1 mm, (b) depth of cut 2 mm, and (c) depth of cut 3 mm.



**Figure 9:** Influence of cutting speed on surface roughness at constant depth of cut 2 mm: (a) fiber orientation 30°, (b) fiber orientation 60°, and (c) fiber orientation 90°.



**Figure 10:** Influence of feed rate on surface roughness at constant depth of cut 2 mm: (a) fiber orientation 30°, (b) fiber orientation 60°, and (c) fiber orientation 90°.



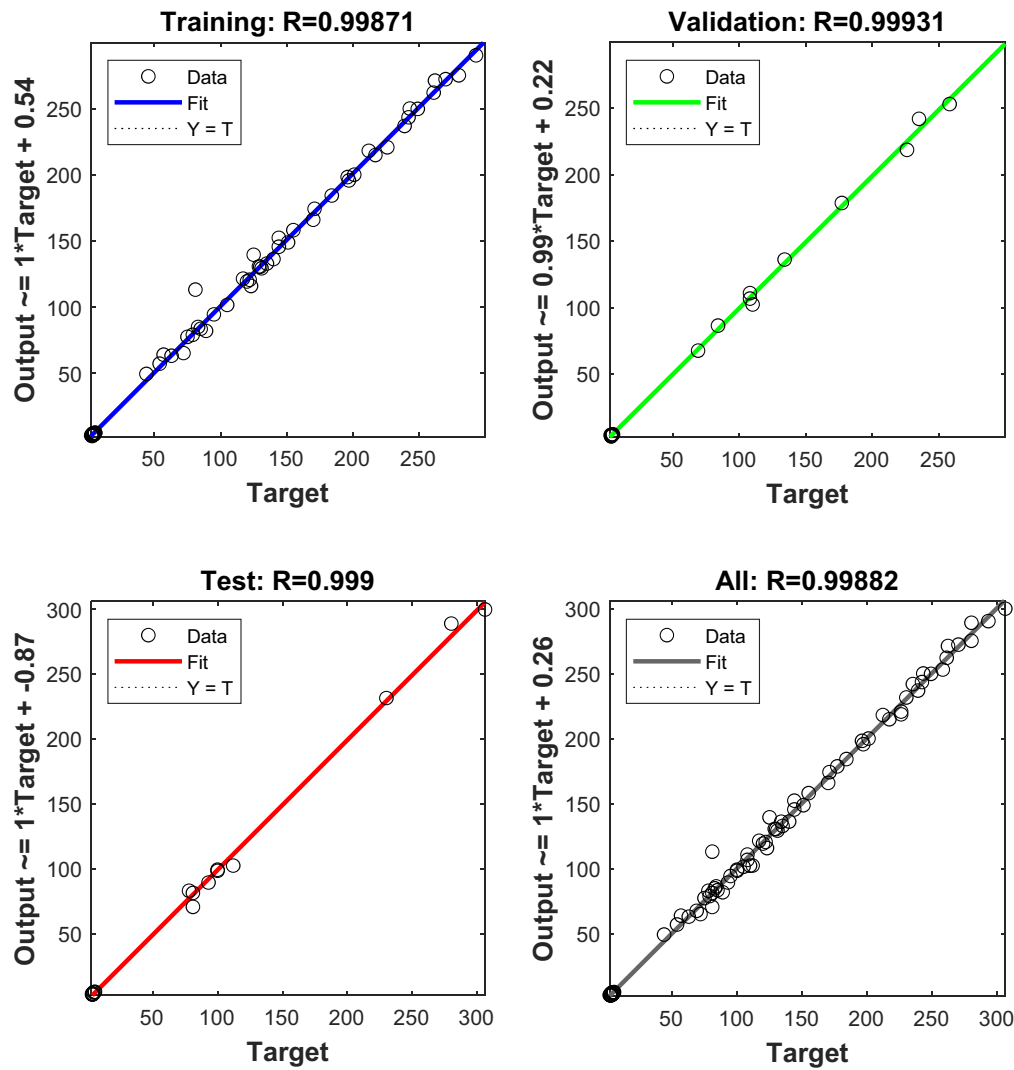


Figure 11: Regression model produced by the ANN model.

Table 3: Results from experimental study and ANN model

Cutting parameters				Experimental results		ANN results		Error (%)	
$a$ (mm)	$V_c$ (m·min <sup>-1</sup> )	$f$ (mm·rev <sup>-1</sup> )	Orientation angle (°)	$F$ (N)	$R_a$ (μm)	$F$ (N)	$R_a$ (μm)	$F$ (N)	$R_a$ (μm)
1	100	0.1	30	51	2.93	55.56	3.27	8.207	10.397
1	150	0.3	30	72	3.37	81.69	3.69	11.862	8.672
2	100	0.2	30	95	3.6	87.82	3.71	8.176	2.965
3	50	0.1	30	212	3.91	215.63	4.3	1.683	9.069
3	100	0.3	30	247	4.18	256.7	4.7	3.779	11.064
1	50	0.2	60	96	3.92	86.5	4.28	10.983	8.411
1	150	0.1	60	77	3.46	69.87	3.36	10.204	2.976
2	50	0.3	60	158	5.12	173.72	4.89	9.049	4.703
2	150	0.2	60	112	3.76	101.23	4.12	10.639	8.738
3	100	0.1	60	208	4.06	212.07	4.56	1.919	10.965
3	150	0.3	60	244	4.32	254.37	4.63	4.077	6.695
1	100	0.2	90	123	3.99	124.53	4.37	1.229	8.696
2	50	0.1	90	150	4.51	161.92	4.13	7.362	9.2
2	100	0.3	90	184	4.99	185.97	4.9	1.059	1.837
3	50	0.2	90	274	4.94	250.44	4.85	9.407	1.856
3	150	0.1	90	204	4.27	213.68	4.55	4.53	6.154

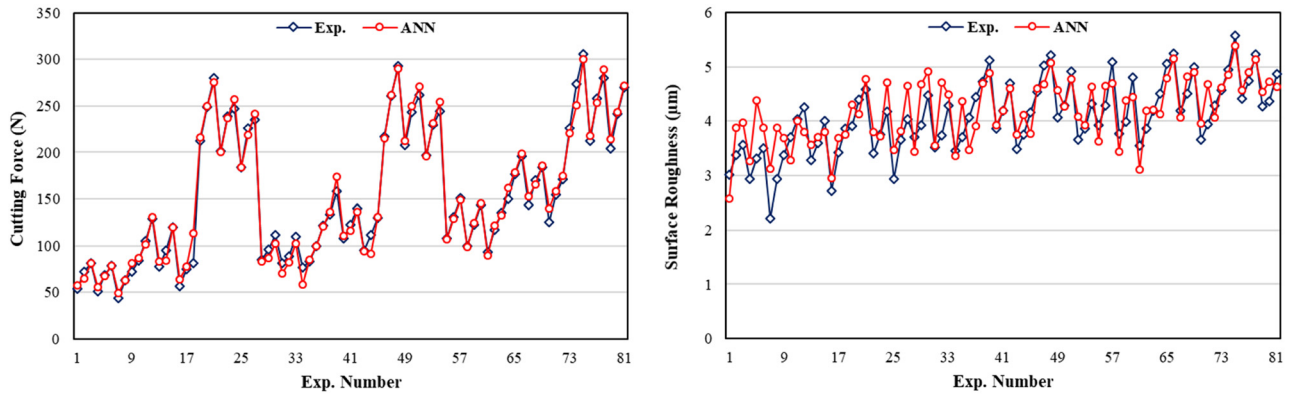


Figure 12: Comparison of experimental data with predicted results from ANN.

surface roughness obtained at high cutting speed was better than that obtained at low cutting speed mainly due to softening in the material's matrix caused by the heat generated in the workpiece at high speeds. The softening matrix material creates chip consisting of cut fibers that are less deformed during processing. Less deformed fibers cut with lower forces produces lower surface roughness [16,17,25,46,47,48].

From these experiments, it was observed that the surface roughness at 3 mm depth of cut was higher than at 1 mm depth of cut, as seen from Figure 8. Depth of cut has little effect on composite machining compared to cutting speed and feed rate [51]; however, higher depth of cut has a detrimental effect on surface quality in GFRP machining and, therefore, it is recommended to use a low depth of cut when machining GFRP composite materials [22,53].

All in all, the highest cutting force (306 N) was obtained at  $0.3 \text{ mm}\cdot\text{rev}^{-1}$  feed rate,  $90^\circ$  fiber orientation angle, 3 mm depth of cut, and  $50 \text{ m}\cdot\text{min}^{-1}$  cutting speed, where, in this case,  $5.58 \mu\text{m}$  surface roughness was obtained. The lowest cutting force (44 N) was obtained at  $0.1 \text{ mm}\cdot\text{rev}^{-1}$  feed rate

(lowest feed rate),  $30^\circ$  fiber orientation angle (minimum fiber orientation angle), 1 mm depth of cut (minimum depth of cut), and  $150 \text{ m}\cdot\text{min}^{-1}$  cutting speed (maximum cutting speed), where, in this case, minimum surface roughness  $2.22 \mu\text{m}$  was obtained.

The maximum surface roughness was obtained at the highest feed rate ( $0.3 \text{ mm}\cdot\text{rev}^{-1}$ ), fiber orientation angle ( $90^\circ$ ), and depth of cut (3 mm), as shown in Figures 8–10, whereas the lowest surface roughness was observed for the lowest feed rate ( $0.1 \text{ mm}\cdot\text{rev}^{-1}$ ), fiber orientation angle ( $30^\circ$ ), and highest cutting speed.

Taking the cutting forces and surface roughness values obtained in the experimental part of the study as supervising reference the ANN model was designed with the input parameters are being the machining parameters used experimentally. For each of stages of the design process (training, validation, testing, and system), the obtained results are plotted and analyzed with regression process as shown in Figure 11, where the regression  $R$  values (on the top) and the linear regression equation ( $Y$ -axis) are shown on each of graphs.

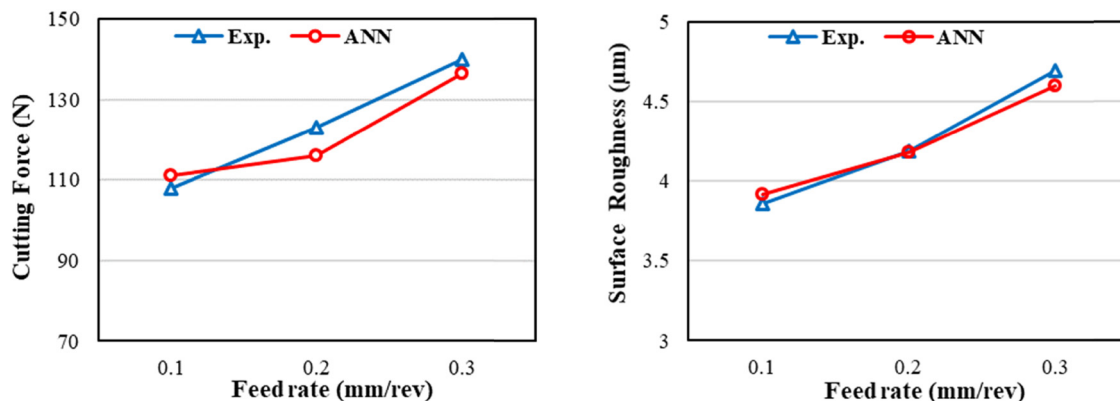


Figure 13: Comparison of experimental data and ANN for depth of cut 2 mm, cutting speed  $100 \text{ m}\cdot\text{min}^{-1}$ , and orientation angle  $60^\circ$ .

**Table 4:** Weight and bias values in ANN model

lw {1,1}-weight to layer 1 from input 1	[−1.2592; −1.5571; −1.8251; 2.0482; −0.023451; −0.26534; 2.2684; 0.23592; 3.6965; 0.02574; −0.15156; 0.2392; 0.28629; −1.7235; 0.000973; −2.356; 0.80023; −0.39529; −1.3232; 0.26572; 0.7197; −0.2348; −2.6517; 0.05095−1.8867; −0.072011; −2.018; 1.0609; −0.67493; −1.2496; −0.33497; −1.1264; −1.1801; −0.23953; −1.7968; 0.67722−1.3526; 0.80845; 0.84801; 1.3338]
b {1}-bias to layer 1	[1.0835; −2.8587; −0.49337; 0.38064; −0.18119; −0.37284; 1.5; −3.4599; −2.473; −2.3537]
lw {2,1}-weight to layer 1	[0.11908; 0.44101; 0.58384; −0.0085291; 0.96606; −0.87526; −0.24475; −0.38488; 0.23032; 0.25378; 0.32094; 0.19434; 0.32731; 0.022901; 0.19761; −0.63468; 0.13446; −0.93047; 0.067842; −0.23836]
b {2}-bias to layer 2	[0.30288; −0.8118]

**Table 5:** Validation results obtained from ANN and experimental study for different input parameters

Cutting parameters				Experimental results		ANN results		Error (%)	
$a$ (mm)	$V_c$ (m·min <sup>−1</sup> )	$f$ (mm·rev <sup>−1</sup> )	Orientation angle (°)	$F$ (N)	$R_a$ (μm)	$F$ (N)	$R_a$ (μm)	$F$ (N)	$R_a$ (μm)
1	90	0.15	30	50.47	3.25	53.89	3.65	6.35	10.96
1.5	130	0.25	60	71.14	4.13	78.47	4.23	9.34	2.36
2	80	0.3	90	177.45	5.01	188.4	5.43	5.81	7.73
2.5	150	0.15	30	112.14	3.29	121.08	3.38	7.38	2.66
3	70	0.2	60	248.56	4.16	259.89	4.61	4.36	9.76
1	120	0.25	90	109.89	4.12	120.07	4.29	8.48	3.96
2	70	0.1	30	85.23	3.4	88.77	3.54	3.98	3.95
2.5	100	0.3	60	245.65	4.33	251	4.71	2.13	8.07
3	140	0.25	90	267.09	4.65	279.4	4.95	4.4	6.06

The results obtained with ANN model for cutting force and surface roughness are given in Table 3. These model-based artificial results are compared to those obtained from the experimental study for cutting force and surface roughness in Figures 12 and 13. From the figures, it is seen that ANN results are well fitted to the ones obtained with experiments. As seen in Figure 11, the confidence coefficient value obtained for ANN model both in training and test phases was 99%, which is higher than 95% accepted in prediction analysis. These results confirmed the suitability of the ANN in modeling the machining process.

The success rate for all cases was above 90%. When the ANN model is trained, the weight vectors going between layers and the bias vector to each layer are shown in Table 4. Table 5 shows the comparison of results produced by ANN and experimental results obtained during the testing of the model. It can be observed that the results obtained from the experimental study and the ones obtained from ANN model are very close to each other. The experimentally obtained cutting force was 140 N at 2 mm depth of cut, 100 m·min<sup>−1</sup> cutting speed, 60° fiber orientation angle, and 0.3 mm·rev<sup>−1</sup> feed rate, whereas the estimated cutting force with ANN was found to be 136.36 N. The surface roughness value obtained experimentally with

the same machining parameters was obtained as 4.7 μm. The estimated value with ANN was found to be 4.60 μm. As can be comprehended, a high agreement of 97.4 and 97.87%, respectively, were observed between the experimental results and ANN results. In both experimental and model-based analysis, the lowest cutting force and surface roughness were achieved at low fiber orientation angle, low feed rate and depth of cut and at high cutting speeds. These highly correlated values are validating the designed ANN model to confidently be used in machining process simulation. With such a model, variety of machining parameters can be tested in GFRP composite materials for obtaining perfect surface with a minimum cutting force.

## 5 Conclusions

In this study, experimental results were obtained by turning GFRP composites from various aspects and an ANN model was developed using these data. With this artificial model, the effects of fiber orientation, cutting speed, feed rate, and depth of cut on the cutting force and surface roughness values were estimated. While developing the model, orientation angle, cutting speed,

feed rate, and depth of cut were taken as input features and fed to the input of the ANN model. The output was cutting force and surface roughness. From this study, the following were deduced.

1. The highest cutting force (306 N) and maximum surface roughness (5.58  $\mu\text{m}$ ) were obtained at maximum feed rate (0.3 mm·rev<sup>-1</sup>), fiber orientation (90°), depth of cut (3 mm), and minimum cutting speed (50 m·min<sup>-1</sup>).
2. Minimum cutting force (44 N) and surface roughness (2.22  $\mu\text{m}$ ) were obtained at 0.1 mm·rev<sup>-1</sup> feed rate (lowest feed rate), 30° fiber orientation angle (minimum fiber orientation angle), 1 mm depth of cut (minimum depth of cut), and 150 m·min<sup>-1</sup> cutting speed (maximum cutting speed).
3. Increasing fiber orientation angle, feed rate and depth of cut increased the cutting force and surface roughness.
4. Increasing the cutting speed decreased the cutting force and surface roughness.
5. The values obtained from ANN were very close to the data obtained from experimental studies.
6. From the results obtained from the experiments and ANN model, it is confirmed that the developed model can be used effectively to predict cutting force and surface roughness with respect to variations in machining parameters including fiber's orientation angle.
7. ANN model had predicted cutting force and surface roughness values accurately.

**Funding information:** This study received no external funding.

**Author contribution:** The author has accepted responsibility for the entire content of this article and approved its submission.

**Conflict of interest:** The author (Ahmet Yardimeden) declares that there is no conflict of interest.

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