



Sustainable Optimization of Abrasive Water Jet Machining of Green $\text{ZrO}_2\text{--La}_2\text{O}_3$ Modified Sugarcane/Bamboo Fibre Epoxy Composites Using Taguchi–ANOVA–ANN

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ABSTRACT

A combined Taguchi–ANOVA–ANN approach was employed to assess the abrasive water jet machining behaviour of $\text{ZrO}_2\text{--La}_2\text{O}_3$ -modified sugarcane fibre/bamboo fibre epoxy composites. ZrO_2 was green synthesized from zirconyl oxychloride octahydrate, while La_2O_3 was produced from lanthanum nitrate hexahydrate $[\text{La}(\text{NO}_3)_3 \cdot 6\text{H}_2\text{O}]$, with *Hibiscus sabdariffa* flower extract serving as the green reaction medium. Twenty-seven trials were arranged according to a three-factor, three-level (3^3) factorial scheme. Jet pressure (180–260 MPa), traverse speed (15–45 mm/min), and standoff distance (1.5–4.5 mm) were varied to determine material removal rate (MRR), surface roughness (R_a), and kerf width. The referred conditions were 260 MPa–45 mm/min, 1.5 mm for maximum MRR, 260 MPa–15 mm/min, 1.5 mm for minimum R_a , and 180 MPa–30 mm/min, 1.5 mm for minimum kerf width. ANOVA attributed 75.30% of MRR variation and 57.25% of R_a variation to jet pressure, while standoff distance accounted for 86.92% of kerf-width variation. Bayesian-regularized feed-forward ANN (Artificial Neural Network) models validated through repeated five-fold cross-validation, yielded mean R^2 values of 0.9942, 0.9946, and 0.9583 for MRR, R_a , and kerf width. The integrated framework successfully established parameter effects, response-specific machining settings, and reliable performance predictions for the fabricated composite.

Keywords: Green synthesis; Surface roughness; Kerf width; ANOVA; Artificial neural network.

1. INTRODUCTION

Interest in lightweight, sustainable structures has encouraged epoxy modification with sugarcane and Bamboo fibres. However, water uptake, variable fibre morphology, inadequate interfacial bonding, and machining damage restrict dimensional reliability. These limitations may be reduced using ZrO_2 derived from zirconyl oxychloride octahydrate and La_2O_3 synthesized from lanthanum nitrate hexahydrate $[\text{La}(\text{NO}_3)_3 \cdot 6\text{H}_2\text{O}]$, with *Hibiscus sabdariffa* flower extract enabling green nanoparticle preparation.

Sugarcane fibre is an abundant agro-industrial residue containing cellulose-rich structures capable of reinforcing polymer matrices. Coconut-coir/sugarcane-fibre epoxy composites have demonstrated improved

chemical integration, thermal stability and fibre–matrix bonding, although their flexural performance remained limited (Abdullah *et al.* 2026). Sugarcane-bagasse composites containing rice-husk or wood-powder fillers exhibited greater strength than corresponding unfilled systems (Velmurugan *et al.* 2023). However, sugarcane-containing composites develop porosity and absorb moisture when interfacial compatibility and processing conditions are inadequate, as observed in sugarcane–betel-nut epoxy composites (Sarker *et al.* 2025). These findings emphasize the need to combine sugarcane fibre with a mechanically stronger reinforcement and suitable interfacial modifiers.

Ceramic nanoparticles strengthen the polymer–fibre interface by occupying microvoids, restricting matrix-chain mobility and deflecting propagating cracks.

ZrO₂ is particularly attractive because of its hardness, chemical stability, fracture resistance and ability to enhance load transfer. Flax–areca-fibre composites containing 7.5 wt.% ZrO₂ exhibited improved tensile, flexural, impact and interlaminar properties, together with enhanced thermal stability (Prabhu *et al.* 2025). ZrO₂-containing casuarina-fibre composites demonstrated improved mechanical and tribological behaviour (Barve *et al.* 2025). Johnson *et al.* (2025) reported that dispersed ZrO₂ enhanced interfacial load transfer in peepal-fibre/epoxy composites.

La₂O₃ is another potentially useful oxide modifier because it can influence interfacial structure, thermal stability and reinforcement rigidity. Incorporating La₂O₃ into continuous basalt fibres produced a denser structural network and increased fibre strength and elastic modulus by 53.36% and 31.76%, respectively (Geng *et al.* 2025). Lanthanum modification also enhanced the flexibility, tensile behaviour and surface properties of Al₂O₃ nanofibre membranes at an appropriate concentration, whereas excessive addition reduced their mechanical performance (Feng *et al.* 2026). These findings indicate that controlled La₂O₃ incorporation may complement the hardness and crack-resistance contribution of ZrO₂ in hybrid epoxy composites.

Conventional nanoparticle synthesis frequently involves toxic reagents, high energy consumption and hazardous reaction by-products. Plant-mediated synthesis offers a more sustainable route because phytochemicals can act as complexing, hydrolysis-controlling and stabilizing agents. *Hibiscus sabdariffa* flower extract contains polyphenols, flavonoids, anthocyanins and organic acids capable of assisting nanoparticle formation and restricting excessive particle growth. Its effectiveness in producing stable metal and metal-oxide nanoparticles has been demonstrated through the green synthesis of ZnO, Au and Au/ZnO nanostructures with controlled morphology and nanoscale dimensions (Shochah and Jabir, 2024).

Despite their favourable properties, heterogeneous natural-fibre composites were difficult to machine by conventional cutting techniques because fibre pull-out, matrix cracking, delamination, burr formation and excessive tool wear can occur. Abrasive water-jet machining (AWJM) is a non-contact process that minimizes thermal damage and is capable of cutting fibre-reinforced composites with complex geometries. Its performance is primarily governed by traverse speed, jet pressure, abrasive conditions and stand-off distance, while nanoparticle additives can improve interfacial adhesion and suppress machining damage (Rasu *et al.* 2024). However, increasing stand-off distance promotes jet divergence and kinetic-energy dissipation, whereas unsuitable traverse speed may cause incomplete cutting or excessive erosion.

Recent investigations have employed statistical and machine-learning techniques to describe the nonlinear relationships between AWJM factors and machining responses. Response Surface Methodology–Artificial Neural Network (RSM–ANN) optimization of banana–paddy-straw composites identified abrasive flow rate, stand-off distance conditions and traverse speed that minimized surface roughness (R_a) and kerf angle (Sengottaiyan *et al.* 2026). Similarly, combined grey relational analysis coupled with principal component analysis and machine-learning models reduced kerf-ratio error, surface roughness and delamination in pumice-filled banana-fibre sandwich composites (Chenrayan *et al.* 2025). Nevertheless, conventional statistical models may not adequately capture the coupled effects of fibre hybridization, nanoparticle loading and AWJM parameters.

Recent studies have demonstrated the effectiveness of statistical and machine-learning techniques in predicting the performance of fiber-reinforced composites. Nanoclay incorporation was found to reduce wear loss in glass- and bamboo-fiber epoxy composites, while ANN provided better predictive accuracy than RSM (Ahmad *et al.* 2025). Chemical treatment parameters significantly influenced the tensile strength of bamboo fibers, with ANN outperforming RSM–box–Behnken design in prediction performance (Makhatha *et al.* 2025). Water absorption in plantain-peel- and bamboo-fiber polystyrene composites was successfully modeled using ANN, achieving R^2 values above 0.98 (Ighalo *et al.* 2021).

The literature demonstrates the individual potential of sugarcane fibre, bamboo, ZrO₂ and La₂O₃; however, their combined application in a single epoxy composite and the corresponding AWJM behaviour remain insufficiently established. In particular, limited information is available regarding how green-synthesized ZrO₂–La₂O₃ nanoparticles influence the material-removal and damage mechanisms of sugarcane–bamboo hybrid laminates. The simultaneous prediction of material removal rate, surface roughness and kerf characteristics for this material system also requires further investigation.

The novelty of this study lies in the development and AWJM evaluation of a sugarcane–bamboo/epoxy hybrid composite reinforced with green-synthesized ZrO₂–La₂O₃ nanoparticles. The incorporation of *Hibiscus sabdariffa*-assisted ZrO₂ and La₂O₃ into a hybrid natural-fibre epoxy system provides a distinctive material configuration for abrasive water jet machining. In addition, the study integrates Taguchi S/N analysis, ANOVA (Analysis of Variance), and artificial neural network modelling within a unified machining framework. Taguchi analysis determines response-specific favourable machining conditions, ANOVA quantifies the influence of jet pressure, traverse speed,

and standoff distance, and independently trained ANN models predict Material removal rate (MRR), surface roughness, and kerf width using repeated five-fold cross-validation. Thus, the work combines green nanoparticle synthesis, hybrid natural-fibre composite development, statistical machining optimization, and data-driven prediction to provide a comprehensive approach for evaluating and controlling the AWJM performance of the developed composite.

2. MATERIALS AND METHODS

2.1 Materials

Sugarcane fibre and bamboo fibre served as the two bio-reinforcements, with their proportion fixed at 60:40 by weight within the fibre fraction. Araldite LY536 epoxy and HY951 hardener formed the polymer matrix at a 10:1 weight ratio. Zirconyl oxychloride octahydrate ($\text{ZrOCl}_2 \cdot 8\text{H}_2\text{O}$) and lanthanum nitrate hexahydrate [$\text{La}(\text{NO}_3)_3 \cdot 6\text{H}_2\text{O}$] supplied the zirconium and lanthanum ions required for producing ZrO_2 and La_2O_3 , respectively. *Hibiscus sabdariffa* flower extract provided the natural reaction medium for the synthesis processes.

2.2 Green Synthesis of ZrO_2 Nanoparticles and La_2O_3 Nanoparticles

The plant extract was produced by dispersing 20 g of washed, shade-dried *Hibiscus sabdariffa* flower

powder in 200 mL of distilled water. This suspension was maintained at 70–80 °C for 30 minutes, allowed to cool, filtered, and refrigerated at 4 °C until utilization (Hameed *et al.* 2026). Individual 0.1 M precursor solutions were prepared by dissolving 6.45 g of $\text{ZrOCl}_2 \cdot 8\text{H}_2\text{O}$ and 8.66 g of $\text{La}(\text{NO}_3)_3 \cdot 6\text{H}_2\text{O}$ separately in 200 mL of distilled water.

For each synthesis, 50 mL of flower extract was introduced slowly into the corresponding salt solution while stirring continuously at 70 °C. After 30 minutes, 1.0 M NaOH was used to raise the pH to approximately 10.0 for the zirconium mixture and 10.5 for the lanthanum mixture. Stirring was continued for another 2 hours, followed by 12 hour room-temperature ageing to promote hydroxide-precursor development.

Both precipitates were recovered independently through centrifugation at 8000 rpm for 10 minutes, washed with deionized water and ethanol, and dried at 80–90 °C for 12 hours. Thermal conversion of the zirconium-based precursor at 500 °C for 3 hours yielded ZrO_2 , whereas calcination of the lanthanum-based precursor at 650 °C for 3 hours produced La_2O_3 . After grinding and sieving, the estimated particle-size intervals were 40–70 nm for ZrO_2 and La_2O_3 . Bioactive compounds present in the flower extract assisted metal-ion complexation, particle stabilization, and controlled oxide formation. Fig. 1 shows the synthesized nanoparticles.

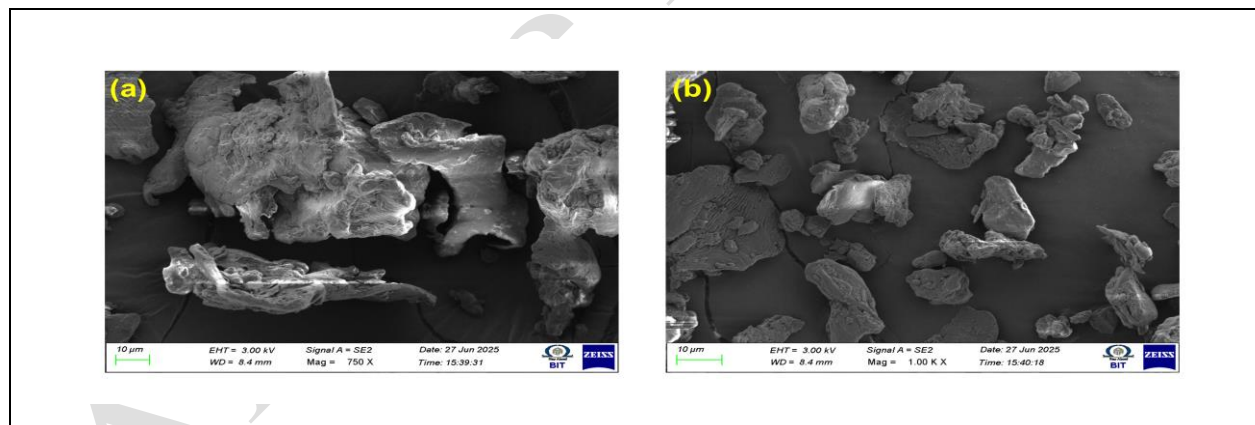


Fig. 1: Green-synthesized (a) ZrO_2 and (b) La_2O_3 nanoparticles

Prior to composite preparation, both nanopowders were conditioned at 80–100 °C to eliminate surface-bound moisture. ZrO_2 and La_2O_3 were blended in equal proportions, producing a combined reinforcement concentration of 6 wt.%. The blended particles were incorporated into LY536 resin through mechanical agitation for 20–30 minutes and ultrasonication for 15–20 minutes (Yao *et al.* 2026). HY951 was subsequently introduced while retaining the 10:1 resin-to-hardener ratio.

The filler-free formulation contained 18 wt.% sugarcane fibre, 12 wt.% bamboo fibre, and 70 wt.% epoxy system. The nanoparticle-modified formulation comprised 14.4 wt.% sugarcane fibre, 9.6 wt.% bamboo fibre, 6 wt.% combined ZrO_2 – La_2O_3 , and 70 wt.% epoxy system. Consequently, the 60:40 sugarcane fibre-to-bamboo fibre ratio remained unchanged in both formulations.

2.3 Experimental Setup and Design

Machining trials were performed on a CNC (Computer Numerical Control) abrasive water jet fitted with high-pressure pump having a maximum operating capacity of 400 MPa (Rout *et al.* 2022). Garnet abrasive was delivered at approximately 0.35 kg min^{-1} and combined with the pressurized water before passing through a sapphire orifice. Traverse speed, standoff distance and jet pressure were regulated through the CNC controller.

Material removal rate was evaluated from specimen mass loss using an analytical balance with $\pm 0.001 \text{ g}$ readability and $\pm 0.002 \text{ g}$ linearity (Madival *et al.* 2023). Before each measurement, the machined specimens were cleaned using compressed air and conditioned for 15 minutes. The MRR was obtained by dividing the difference between initial and final masses by the corresponding machining duration.

Average surface roughness was determined with Mitutoyo surface-roughness following ISO 4287:1997. The instrument operated with a $0.01 \text{ }\mu\text{m}$ resolution, 0.8 mm cutoff length, and $5 \text{ }\mu\text{m}$ stylus-tip radius (Avinash *et al.* 2022). Three readings were collected perpendicular to the jet-travel direction at separate positions, and their mean was calculated.

Kerf width was quantified using calibrated optical image analysis at $50\times$ magnification (Kumar and Babu, 2024). Calibration was performed with a stage micrometer marked at $10 \text{ }\mu\text{m}$ intervals. Width measurements were obtained from the entry, central, and exit sections of each kerf, after which the average value was recorded.

The investigated factors were jet pressure at 180, 220, and 260 MPa; traverse speed at 15, 30, and 45 mm min^{-1} ; and standoff distance at 1.5, 3.0, and 4.5 mm. Combining these levels generated a 3^3 full-factorial matrix containing 27 machining conditions that measured MRR, R_a , and kerf-width.

2.4 Experimentation

The machining programme was applied to the unfilled sugarcane fibre/bamboo fibre epoxy composite and the corresponding composite containing 6 wt.% $\text{ZrO}_2\text{--La}_2\text{O}_3$. The ceramic reinforcement consisted of ZrO_2 prepared from zirconyl oxychloride octahydrate and La_2O_3 produced from lanthanum nitrate hexahydrate [$\text{La}(\text{NO}_3)_3 \cdot 6\text{H}_2\text{O}$], with *Hibiscus sabdariffa* flower extract used during both green synthesis routes.

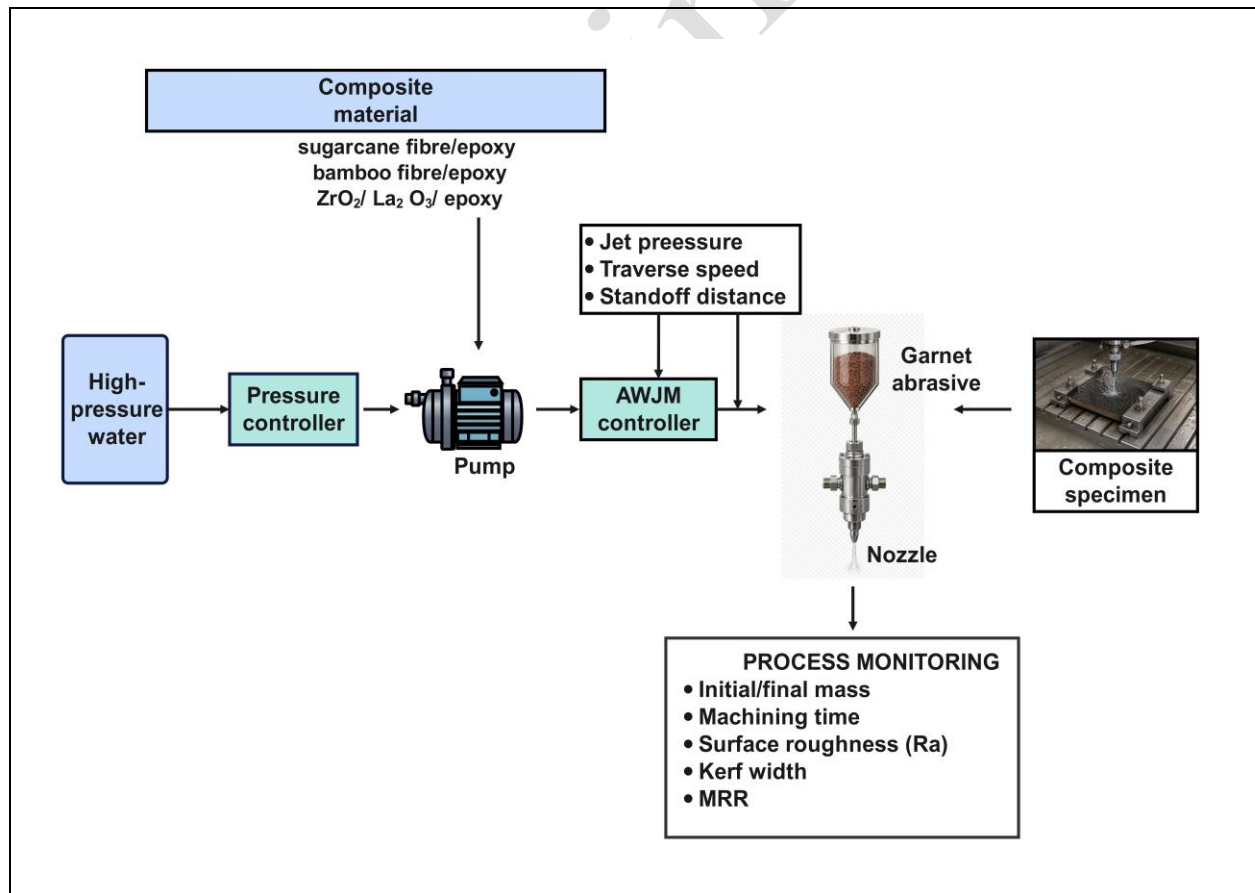


Fig. 2: AWJM processing of both composite configurations

Before machining, every specimen was cleaned, dried, and weighed to establish its initial mass. The required traverse speed, standoff distance and jet pressure were assigned according to the experimental matrix (Jani *et al.* 2024). Nozzle geometry, garnet type, and abrasive delivery rate were maintained consistently, while the three selected machining parameters were varied between trials. Each workpiece was secured to the machining table using a bolted fixture before initiating the programmed cutting path. Following machining, the specimen was detached, rinsed, cleaned with compressed air, and conditioned before its final mass was recorded. The observed mass reduction and machining duration were used to calculate the MRR. R_a and kerf width were evaluated using the profilometric and optical procedures. Identical measurement practices were followed for both composite configurations to permit direct performance comparison. The complete experimental sequence is illustrated in Fig. 2.

2.5 Taguchi Optimization and ANN Modelling

A 3^3 full-factorial design with 27 machining conditions was employed to investigate effects of jet pressure, traverse speed, and standoff distance on AWJM performance of ZrO_2 - La_2O_3 -filled sugarcane-bamboo/epoxy composite. The three factors were varied at three levels: jet pressure at 180, 220, and 260 MPa, traverse speed at 15, 30, and 45 mm/min, and standoff distance at 1.5, 3.0, and 4.5 mm. The measured responses were surface roughness, material removal rate, and kerf width. Selected machining parameters and corresponding levels are presented in Table 1.

Table 1. AWJM process parameters and levels

Factor	Process Parameter	Unit	Level 1	Level 2	Level 3
A	Jet pressure	MPa	180	220	260
B	Traverse speed	mm/min	15	30	45
C	Standoff distance	mm	1.5	3.0	4.5

The 27 machining conditions covered all combinations of three factors and three levels. Surface roughness, material removal rate, and kerf width were considered as response variables. Experimental matrix used for subsequent Taguchi, ANOVA, and ANN analyses is presented in Table 2.

Table 2. Experimental matrix and machining response

Run	Jet Pressure (MPa)	Traverse Speed (mm/min)	Standoff Distance (mm)	MRR (g/min)	R_a (μ m)	Kerf Width (mm)
1	180	15	1.5	146.8	4.86	0.928
2	220	15	1.5	201.6	4.43	0.966
3	260	15	1.5	257.9	4.05	1.008
4	180	30	3.0	160.7	5.42	1.012
5	220	30	3.0	218.5	4.92	1.056

6	260	30	3.0	276.3	4.51	1.098
7	180	45	4.5	167.4	6.03	1.142
8	220	45	4.5	228.8	5.51	1.181
9	260	45	4.5	291.6	5.08	1.224
10	180	15	3.0	129.5	5.12	1.026
11	220	15	3.0	185.9	4.68	1.069
12	260	15	3.0	243.7	4.26	1.111
13	180	30	4.5	143.2	5.71	1.124
14	220	30	4.5	201.4	5.19	1.167
15	260	30	4.5	262.1	4.76	1.209
16	180	45	1.5	199.3	5.53	0.876
17	220	45	1.5	259.8	5.02	0.917
18	260	45	1.5	322.6	4.58	0.958
19	180	15	4.5	112.6	5.39	1.126
20	220	15	4.5	168.7	4.94	1.168
21	260	15	4.5	226.4	4.53	1.211
22	180	30	1.5	177.9	5.17	0.896
23	220	30	1.5	236.2	4.68	0.938
24	260	30	1.5	296.8	4.27	0.979
25	180	45	3.0	182.4	5.77	1.038
26	220	45	3.0	243.5	5.26	1.079
27	260	45	3.0	306.7	4.82	1.121

2.6 Taguchi S/N Ratio Analysis

The response data was analyzed by Taguchi signal-to-noise (S/N) ratio approach. The material removal rate was evaluated using the larger-the-better criterion because a higher MRR is desirable for machining productivity. In contrast, R_a and kerf width were evaluated using the smaller-the-better criterion to favour the improved surface finish and reduced kerf formation.

For MRR, the larger-the-better S/N ratio was calculated (Sheela and Hari, 2026) as follows.

$$S/N = -10 \log_{10} \left[\frac{1}{n} \sum_{i=1}^n \frac{1}{y_i^2} \right]$$

where, the smaller-the-better criterion for R_a and kerf width was calculated as

$$S/N = -10 \log_{10} \left[\frac{1}{n} \sum_{i=1}^n y_i^2 \right]$$

where, y_i was response value and n was number of observations. Main-effects plots for the means and S/N ratios was generated to evaluate effect of all machining parameters and determine the favourable factor levels for each response.

2.6.1 Analysis of Variance

The ANOVA were performed separately for MRR, R_a , and kerf width to determine statistical influence of machining parameters. Jet pressure, standoff distance, and traverse speed were considered as fixed factors. The significance of each factor was evaluated using the F-value and p-value at 95% confidence level, with $p < 0.05$ significant. Percentage contribution of each factor was also calculated to quantify its relative influence on the corresponding machining response. Residual plots, including residual-*versus*-fitted, normal probability, residual-*versus*-order plots, and histogram, were examined to assess the adequacy of the statistical models.

2.7 ANN Modelling

Artificial neural network models were developed to predict AWJM responses from machining parameters. Traverse speed, jet pressure, and standoff distance were used as the three input variables, while MRR, R_a , and kerf width were considered as separate target responses. An independent feed-forward ANN was developed for each response (Sonya *et al.* 2025).

Each network consisted of three input neurons, one hidden layer with two neurons, and one output neuron, resulting in a 3–2–1 network architecture. A hyperbolic tangent sigmoid (Tansig) transfer function was used in hidden layer, while a linear (Purelin) function was employed for output layer. Networks were trained by Bayesian regularization algorithm to control model complexity and improve prediction generalization. Table 3 shows the ANN modelling framework.

2.7.1 ANN Validation and Performance Evaluation

The predictive capability of ANN models was evaluated by repeated five-fold cross-validation. In each repetition, the dataset was divided as five subsets; four subsets were used for model training and remaining subset were used for validation. The procedure continued until all subsets served once as validation set. Complete five-fold cross-validation procedure was repeated 10 times to reduce the influence of individual data partitioning.

Input and output normalization was performed using parameters obtained from the training data within each fold (Arunkumar *et al.* 2024). Model performance was evaluated using the coefficient of determination (R^2), mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). Cross-validated predicted values were subsequently compared with the corresponding machining response values using regression and run-wise comparison plots.

Table 3. ANN modelling framework

Parameter	Specification
Input variables	Jet pressure, traverse speed, standoff distance
Target responses	MRR, R_a , kerf width
ANN approach	Separate network for each response
Network architecture	3–2–1
Hidden layers	1
Hidden neurons	2
Hidden-layer	Tansig
Output-layer	Purelin
Training algorithm	Bayesian regularization
Validation method	Repeated 5-fold cross-validation
Cross-validation repetitions	10
Performance measures	R^2 , MSE, RMSE, MAE, MAPE

3. RESULTS AND DISCUSSION

3.1 Effect of AWJM Parameters on Machining Responses

Machining responses varied considerably with traverse speed, standoff distance and jet pressure. Material removal rate raised predominantly with jet pressure, whereas surface roughness was reduced at higher pressure and increased with traverse speed and standoff distance. Kerf width showed its strongest dependence on standoff distance. These variations indicate that the three responses were governed by different combinations of the AWJM parameters.

For MRR, the mean response increased from 157.8 g/min at 180 MPa to 216.0 g/min at 220 MPa and 276.0 g/min at 260 MPa. Traverse speed also increased the mean MRR from 185.9 to 244.7 g/min between 15 and 45 mm/min. In contrast, increasing standoff distance from 1.5 to 4.5 mm reduced mean MRR from 233.2 to 200.2 g/min. The increase in MRR with pressure was attributed to greater kinetic energy of abrasive stream, which intensified matrix erosion and fibre fracture. At larger standoff distances, jet spreading and energy dissipation reduced the effective impact intensity on the composite surface.

Surface roughness showed an inverse relationship with jet pressure. Mean R_a decreased from 5.444 μm at 180 MPa to 4.959 μm at 220 MPa and 4.540 μm at 260 MPa. Conversely, increasing traverse speed from 15 to 45 mm/min increased R_a from 4.696 to 5.289 μm , and raising standoff distance from 1.5 to 4.5 mm increased R_a from 4.732 to 5.238 μm . Higher jet pressure therefore promoted a more uniform cutting action, whereas reduced interaction time at high traverse speed and greater jet divergence at large standoff distance resulted in comparatively rougher surfaces.

Kerf width was particularly sensitive to standoff distance. Its mean value increased from 0.9407 mm at 1.5 mm to 1.0678 mm at 3.0 mm and 1.1724 mm at 4.5 mm. Increasing jet pressure also increased the mean kerf width from 1.0187 to 1.1021 mm. Traverse speed produced only a limited variation, with mean kerf widths of 1.0681, 1.0532, and 1.0596 mm at 15, 30, and 45 mm/min, respectively. The pronounced increase with standoff distance is associated with expansion of the jet footprint before impingement, resulting in a wider cutting region.

3.2 Taguchi Analysis of MRR

Main-effects plots for mean and S/N ratio of MRR are presented in Fig. 3. The response increased consistently with traverse speed and jet pressure but decreased with standoff distance. The S/N delta values were 4.93, 2.49, and 1.43 for traverse speed, jet pressure, and standoff distance, respectively. Accordingly, jet

pressure was ranked first, followed by standoff distance and traverse speed (Table 4).

Table 4. Taguchi response analysis for MRR

Parameter	Mean L1	Mean L2	Mean L3	Delta	Rank	S/N Delta	S/N Rank
Jet pressure	157.8	216.0	276.0	118.3	1	4.93	1
Traverse speed	185.9	219.2	244.7	58.8	2	2.49	2
Standoff distance	233.2	216.4	200.2	33.0	3	1.43	3

The larger-the-better S/N response identified 260 MPa jet pressure, 45 mm/min traverse speed, and 1.5 mm standoff distance as the optimum combination for maximizing MRR. The dominance of pressure indicates that increasing the energy delivered to the cutting zone has a greater effect on material removal than changes in traverse speed or nozzle position.

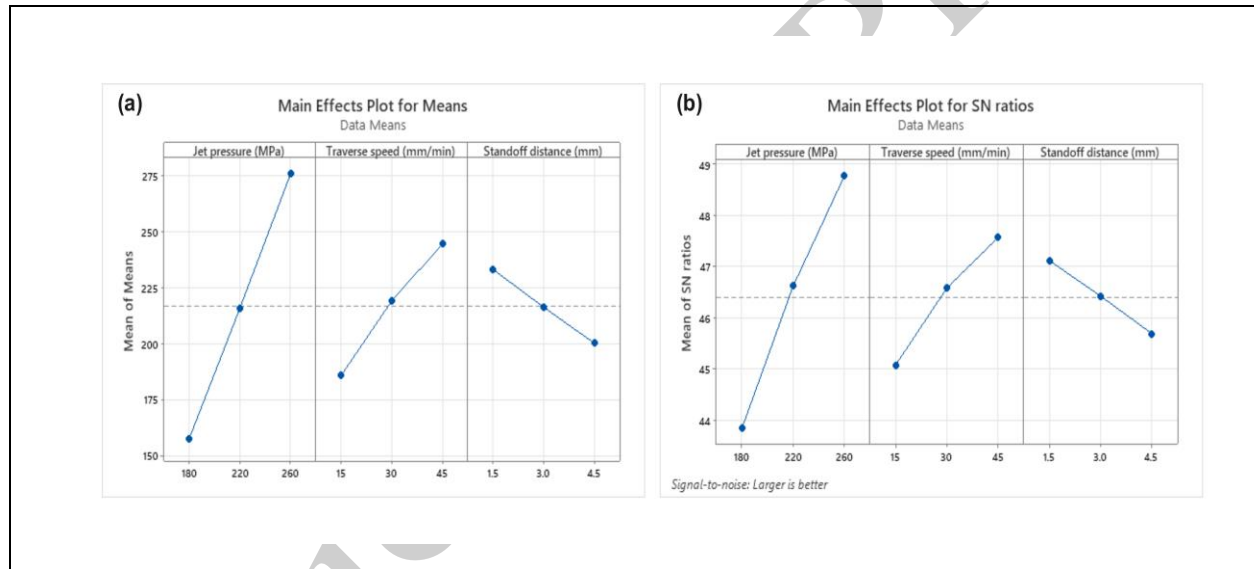


Fig. 3: Main-effects plot for (a) mean material removal rate and (b) S/N ratio of MRR with traverse speed, standoff distance and jet pressure

3.3 Taguchi Analysis of Surface Roughness

Main-effect analysis for R_a is presented in Fig. 4. Increasing jet pressure progressively reduced surface roughness, whereas increasing standoff distance and traverse speed raised R_a . The S/N delta values for traverse speed, standoff distance and jet pressure, were 1.58, 1.04, and 0.89, respectively, giving the same factor ranking as the mean-response analysis (Table 5).

Table 5. Taguchi response analysis for surface roughness

Parameter	Mean L1	Mean L2	Mean L3	Delta	Rank	S/N Delta	S/N Rank
Jet pressure	5.444	4.959	4.540	0.904	1	1.58	1

Parameter	Mean L1	Mean L2	Mean L3	Delta	Rank	S/N Delta	S/N Rank
Traverse speed	4.696	4.959	5.289	0.593	2	1.04	2
Standoff distance	4.732	4.973	5.238	0.506	3	0.89	3

The smaller-the-better criterion indicated an optimum combination of 260 MPa jet pressure, 1.5 mm standoff distance, and 15 mm/min traverse speed. The combination of high pressure and low traverse speed provides greater abrasive interaction with the workpiece, while the minimum standoff distance limits jet divergence. An earlier study illustrates the substantial improvement in surface finish achieved with the use of fillers in the AWJM process, emphasizing their critical role in optimizing surface quality (Grine *et al.* 2024).

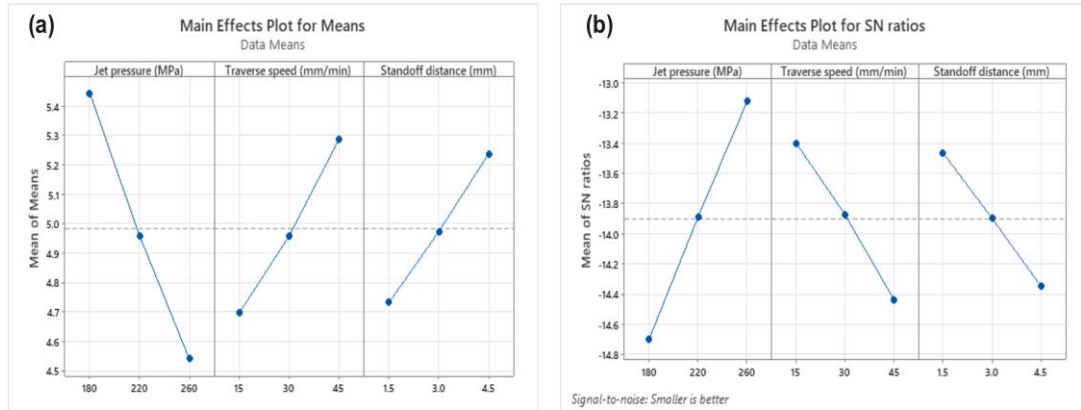


Fig. 4: Main-effect plots (a) mean surface roughness and (b) S/N ratio of surface roughness with jet pressure, traverse speed, and standoff distance

3.4 Taguchi Analysis of Kerf Width

The Taguchi results (Table 6, Fig. 5) for kerf width showed a different factor hierarchy. Standoff distance produced the greatest change in both the mean response and S/N ratio. Its S/N delta of 1.9168 was substantially greater than the jet pressure (0.6889) and traverse speed (0.1310).

The optimum parameter combination for minimum kerf width was 30 mm/min traverse speed, 180 MPa jet pressure and 1.5 mm standoff distance. The relatively small variation associated with traverse speed indicates that kerf formation was controlled primarily by standoff distance and jet pressure.

Table 6. Taguchi response analysis for kerf width

Parameter	Mean L1	Mean L2	Mean L3	Delta	Rank	S/N Delta	S/N Rank
Jet pressure	1.0187	1.0601	1.1021	0.0834	2	0.6889	2
Traverse speed	1.0681	1.0532	1.0596	0.0149	3	0.1310	3
Standoff distance	0.9407	1.0678	1.1724	0.2318	1	1.9168	1

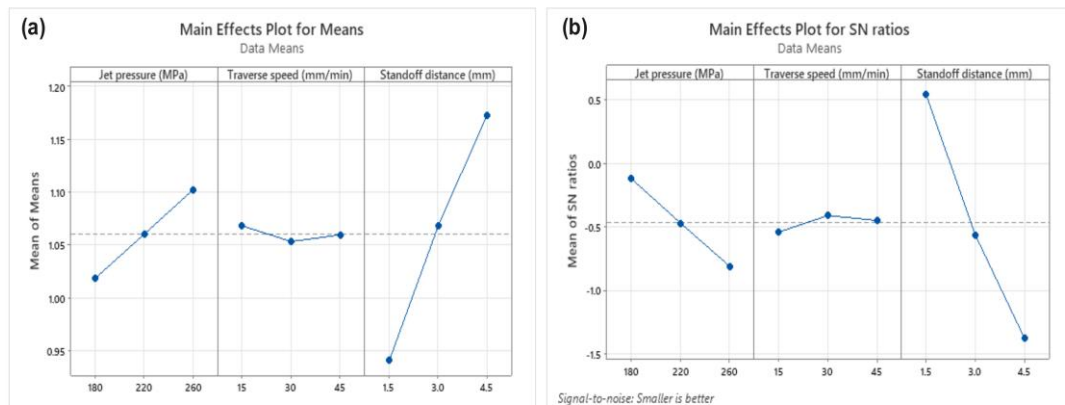


Fig. 5: Main-effects plots (a) mean kerf width and (b) S/N ratio of kerf width with respect to jet pressure, traverse speed, and standoff distance

3.5 Analysis of Variance

ANOVA results for the three machining responses are summarized in Table 7. Jet pressure was the dominant parameter for both MRR and R_a . For MRR, pressure contributed 75.30%, followed by traverse speed at 18.71% and standoff distance at 5.85%. All three parameters were significant at $p < 0.001$.

For surface roughness, jet pressure contributed 57.25%, followed by traverse speed (24.70%) and standoff distance (17.87%). The three parameters were statistically significant at $p < 0.001$, confirming that surface quality was affected by changes in all three machining variables (Subbarao *et al.* 2026).

Kerf width was predominantly controlled by standoff distance, which contributed 86.92% of the total variation. Jet pressure contributed 11.23%, whereas traverse speed accounted for only 0.36%. Standoff distance and jet pressure were significant at $p < 0.001$, while traverse speed was statistically nonsignificant ($p = 0.115$).

Table 7. ANOVA results for MRR, surface roughness, and kerf width

Response	Parameter	Contribution (%)	F-value	p-value
MRR	Jet pressure	75.30	5743.04	<0.001
	Traverse speed	18.71	1427.24	<0.001

Response	Parameter	Contribution (%)	F-value	p-value
R_a	Standoff distance	5.85	446.37	<0.001
	Jet pressure	57.25	3154.92	<0.001
	Traverse speed	24.70	1361.01	<0.001
	Standoff distance	17.87	984.66	<0.001
Kerf width	Jet pressure	11.23	75.16	<0.001
	Traverse speed	0.36	2.41	0.115
	Standoff distance	86.92	581.68	<0.001

The fitted models showed R^2 values of 99.87%, 99.82%, and 98.51% for MRR, R_a , and kerf width, respectively. The corresponding predicted R^2 values were 99.76%, 99.67%, and 97.28%, indicating close agreement between the fitted and predicted response variations (Table 8, Fig. 6).

Table 8. Statistical adequacy of the fitted response models

Response	R^2 (%)	Adjusted R^2 (%)	Predicted R^2 (%)
MRR	99.87	99.83	99.76
Surface roughness	99.82	99.76	99.67
Kerf width	98.51	98.06	97.28

The residual plots for MRR and surface roughness showed residuals distributed around zero without pronounced changes in variance. Kerf width showed comparatively greater residual variation, consistent with its lower model R^2 . Overall, the residual behaviour supported the fitted response trends obtained from the Taguchi and ANOVA analyses.

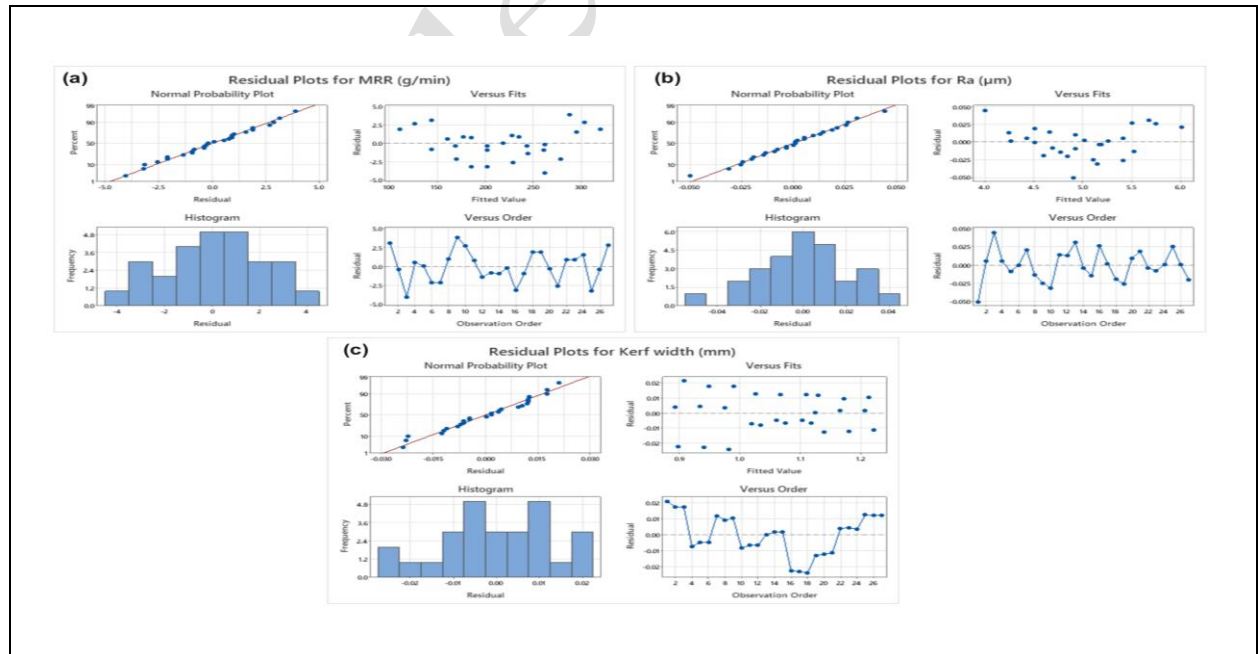


Fig. 6: Residual plots for (a) MRR, (b) surface roughness, and (c) kerf width, including normal probability, residual- versus-fitted, histogram, and residual- versus-order plots

3.6 ANN Prediction of AWJM Responses

Predictive performance of ANN was evaluated for MRR, surface roughness, and kerf width (Table 9,

Fig. 7). The developed models showed close agreement between the response values and their cross-validated predictions. Among the three responses, MRR and surface roughness exhibited the highest predictive accuracy, whereas kerf width showed comparatively greater prediction variability.

The MRR model achieved a mean cross-validated R^2 of 0.9942. The corresponding MSE, RMSE, MAE, and MAPE were 17.827 (g/min)^2 , 4.1986 g/min, 3.3323 g/min, and 1.7147%, respectively. The regression plot in Fig. 7(a) shows close clustering of the predicted MRR values around the ideal agreement line. The low percentage error further indicates that the ANN reproduced the variation in MRR across the machining conditions. In a previous study, eggshell-filled roselle/polyester composites were subjected to AWJM and optimized using an RSM-assisted ensemble of ANN models. The optimum conditions produced a surface roughness of $3.34 \text{ }\mu\text{m}$, MRR of $891.13 \text{ mm}^3 \text{ min}^{-1}$ and kerf angle of 2.57° (Periyappillai *et al.* 2025).

For surface roughness, the ANN achieved the highest mean R^2 of 0.9946. The MSE was $0.001296 \text{ }\mu\text{m}^2$,

while RMSE and MAE were 0.0357 and 0.0292 μm , respectively. The MAPE was 0.5856%, which was the lowest percentage prediction error among the three responses. The regression points in Fig. 7(b) were closely distributed around the ideal prediction line.

The kerf-width model produced a mean R^2 of 0.9584, with MSE, RMSE, and MAE values of 0.000430 mm^2 , 0.0186 mm, and 0.0136 mm, respectively in Fig. 7(c). The MAPE was 1.2916%. Although greater scatter was observed for kerf width than for MRR and R_a , the model retained good overall agreement with the response variation.

Table 9. Cross-validated ANN prediction performance

Response	Mean R^2	SD of R^2	MSE	RMSE	MAE	MAPE (%)
MRR	0.9942	0.0014	17.827	4.1986	3.3323	1.7147
Surface roughness	0.9946	0.0015	0.001296	0.0357	0.0292	0.5856
Kerf width	0.9584	0.0536	0.000430	0.0186	0.0136	1.2916

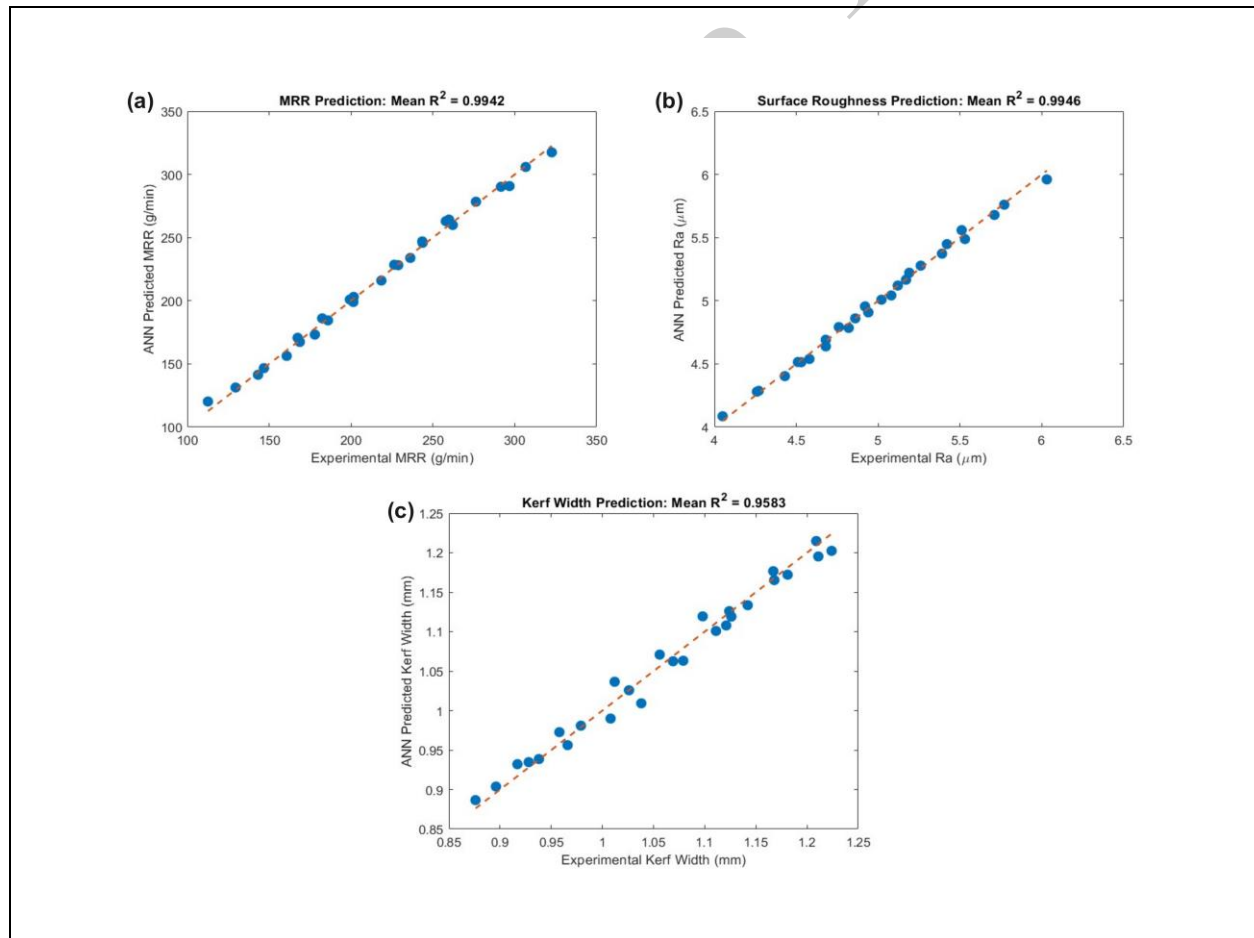


Fig. 7: Cross-validated ANN regression plots among actual and predicted for (a) MRR, (b) surface roughness, and (c) kerf width

3.7 Comparison of Actual and ANN-Predicted Responses

Fig. 8 compares the actual and ANN-predicted responses across the 27 machining runs. For MRR, the predicted curve closely followed the response variation over the entire experimental range. The ANN reproduced both the lower MRR region and the progressive increase toward the maximum response, with only small deviations between actual and predicted values.

A similar agreement was obtained for surface roughness. The predicted R_a values followed the variations observed across the machining runs, consistent

with the R^2 of 0.9946 and MAPE below 1%. The agreement indicates that the influence of traverse speed, pressure and standoff distance at surface roughness was captured effectively by the ANN.

For kerf width, the predicted values followed the overall response profile but showed greater local deviations than MRR and R_a (Vishnoi *et al.* 2025). This behaviour agrees with the comparatively lower R^2 of 0.9584 and higher variation in cross-validation. Nevertheless, the RMSE of 0.0186 mm and MAPE of 1.2916% demonstrate good overall prediction of kerf-width variation.

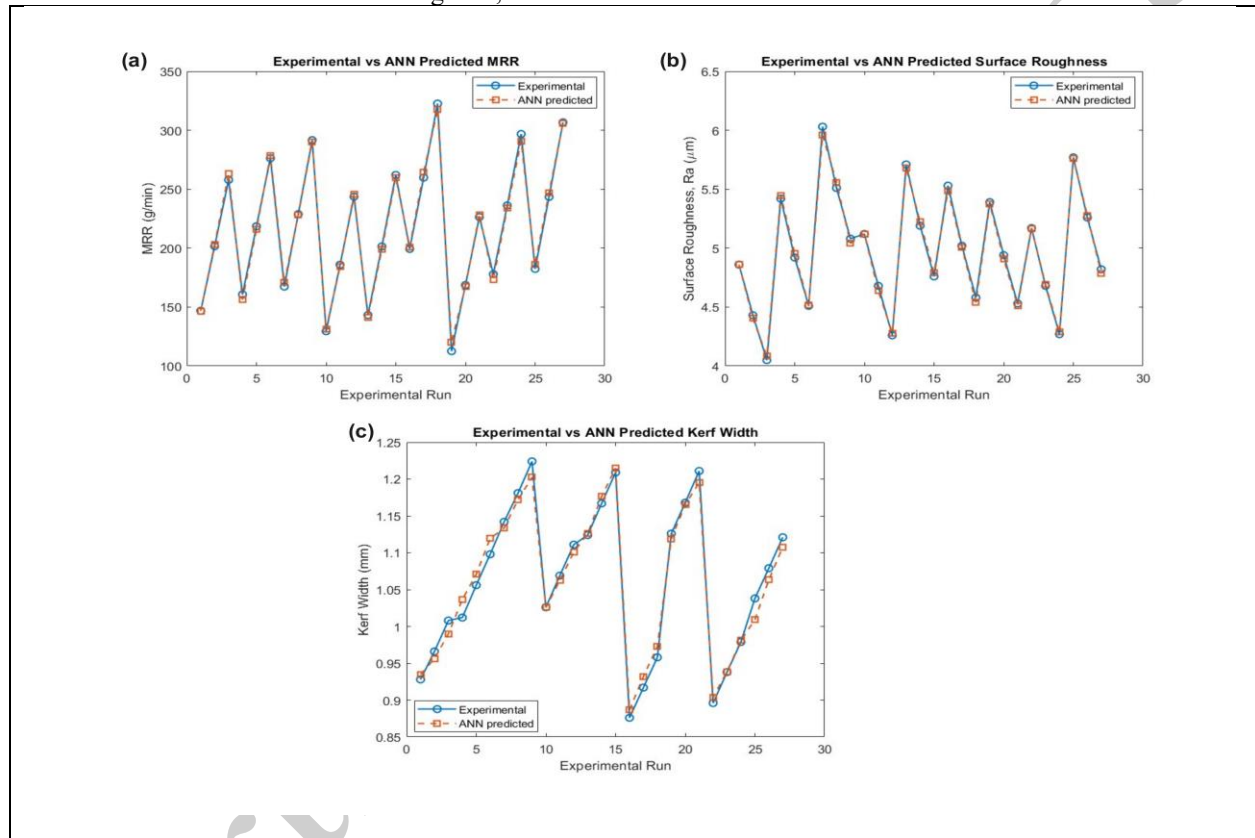


Fig. 8: Comparison of actual and ANN values across the 27 machining runs for (a) material removal rate, (b) surface roughness, and (c) kerf width

3.8 Combined Taguchi–ANOVA and ANN Assessment

The Taguchi and ANOVA results identified different controlling parameters for the three machining responses (Table 10). Jet pressure was the principal parameter affecting MRR and surface roughness, with contributions of 75.30% and 57.25%, respectively. Standoff distance was the dominant factor for kerf width, accounting for 86.92% of its variation.

The optimum conditions obtained from the Taguchi analysis were response-dependent. Maximum MRR was obtained at 260 MPa, 1.5 mm, and 45 mm/min,

whereas minimum surface roughness corresponded to 260 MPa, 1.5 mm, and 15 mm/min. Minimum kerf width was associated with 180 MPa, 1.5 mm and 30 mm/min. A standoff distance of 1.5 mm was therefore consistently favourable for all three responses.

The ANN prediction complemented the Taguchi analysis by providing R^2 values of 0.9942 for MRR, 0.9946 for surface roughness, and 0.9584 for kerf width. The combined analysis demonstrates that Taguchi–ANOVA effectively identifies parameter influence and favourable factor levels, while the ANN captured the relationship between the machining parameters and resulting AWJM responses.

Table 10. Summary of Taguchi–ANOVA and ANN results

Response	Optimum Machining Condition	Dominant Parameter	Contribution (%)	ANN R ²
MRR	260 MPa, 45 mm/min, 1.5 mm	Jet pressure	75.30	0.9942
Surface roughness	260 MPa, 15 mm/min, 1.5 mm	Jet pressure	57.25	0.9946
Kerf width	180 MPa, 30 mm/min, 1.5 mm	Standoff distance	86.92	0.9584

4. CONCLUSION

The machinability of ZrO₂–La₂O₃-modified sugarcane fibre/Bamboo fibre epoxy composites was examined through a combined Taguchi–ANOVA–ANN methodology. Jet pressure, traverse speed, and standoff distance served as control variables, while MRR, R_a, and kerf width represented the performance measures. Maximum MRR occurred at 260 MPa, 1.5 mm, and 45 mm min⁻¹. The lowest R_a corresponded to 260 MPa, 1.5 mm, and 15 mm min⁻¹, whereas minimum kerf width was associated with 180 MPa, 1.5 mm, and 30 mm min⁻¹.

ANOVA assigned 75.30% of MRR variation and 57.25% of R_a variation to jet pressure, confirming its primary influence on both responses. Standoff distance governed kerf width with an 86.92% contribution. Traverse speed accounted for 18.71% of MRR and 24.70% of R_a, but produced a comparatively limited and statistically insignificant effect on kerf width. Therefore, a single parameter combination cannot simultaneously provide the best outcome for every response, making response-dependent setting selection necessary.

Repeated five-fold cross-validation confirmed the predictive reliability of the ANN models. Mean R² values of 0.9942, 0.9946, and 0.9583 were obtained for MRR, R_a, and kerf width with corresponding RMSE values of 4.1986 g min⁻¹, 0.0357 µm, and 0.0186 mm. The strong agreement between experimental and predicted results confirmed that the networks adequately captured AWJM process behaviour. Overall, the combined methodology effectively determines suitable machining conditions, quantifies factor influence, and predicts the AWJM performance of the fabricated composite.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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