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Optimization of Machining Parameters for Ti-6Al-4V Nano-alloy in Abrasive Jet Machining Using Taguchi-Grey Relational Analysis with ANN

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ABSTRACT

The goal of this study is to use a multi-response Taguchi-grey relational technique with Artificial Neural Network (ANN) to optimise the machining parameters of Ti-6Al-4V nano-alloy in the abrasive water jet (AJM) process. The emphasis is on discovering the ideal input factors that have a substantial impact on the workpiece's material removal rate (MRR) and surface quality. The study focuses on the effect of abrasive content characteristics such as SiC volume, SiC size, and abrasive flow rate. Because of its flexibility to handle numerous input variables and produce various sets of optimum values for each response, the Taguchi-grey relational with ANN technique was chosen. The results show that adding SiC in conjunction with garnet enhances the MRR. Images taken with a scanning electron microscope (SEM) show the machined surface of the titanium nano-alloy from several machining attempts. Overall, the Taguchi-grey relational technique is successful for optimising the machining process parameters for Ti-6Al-4V nano-alloy in AJM, resulting in better MRR and surface quality.

Keywords: Ti-6Al-4V nano-alloy; Abrasive water jet; Taguchi-grey relational method; Artificial neural network; Material removal rate; Surface finish.

1. INTRODUCTION

Abrasive Water Jet Machining (AWJM) has emerged as an advanced, non-traditional machining process, particularly valuable for processing hard-to-machine and composite materials due to its ability to cut without inducing significant thermal or mechanical damage. In AWJM, several process parameters, such as pressure, standoff distance, abrasive size and flow rate, nozzle diameter, impingement angle, traverse speed, slurry concentration, and material-specific nano-reinforcement, affect machining responses in nonlinear ways. These responses typically include material removal rate (MRR), surface roughness, kerf/taper, and edge quality. Artificial Neural Networks (ANNs), due to their ability to capture complex, nonlinear relationships, are better suited than linear methods like Taguchi signal-to-noise analysis alone for modeling these interactions. Artificial neural networks act as reliable models, providing realistic multi-objective mapping of input–output relationships. In practice, Taguchi design of experiments can be coupled with Grey Relational Analysis (GRA), which converts multiple normalized responses into a single Grey Relational Grade (GRG). The ANN then learns to map process parameters to these GRGs, enabling accurate prediction across the full parameter space without requiring extensive experimental runs.

Because of this accuracy and versatility, AWJM, where high-pressure water jets transform hydraulic energy into mechanical energy, is increasingly used in industries requiring precise machining of advanced materials. The optimisation of machining parameters, including material removal rate (MRR), kerf width, taper angle, and surface roughness, has been the subject of study for alloys like Ti-6Al-4V, which are essential in aerospace applications due to their high strength-to-weight ratio. Research shows that abrasive characteristics, such as type, size, shape, composition, and flow rate, have a significant impact on machining results. Materials like silicon carbide work well to increase MRR and decrease nozzle wear. As AWJM

responses vary nonlinearly with factors like pressure, standoff distance, nozzle diameter, abrasive size, and flow, impingement angle, traverse speed, slurry concentration, and even nano-reinforcement effects of materials, ANNs are essential. Taguchi optimisation has been widely used to identify influential parameters and determine optimal process conditions.

Unlike linear Taguchi signal-to-noise analysis, ANN effectively captures these complex nonlinear interactions, serving as a high-fidelity surrogate model that can predict multiple responses or GRG derived from Taguchi and GRA, thereby enabling rapid multi-objective prediction and optimisation without the need for extensive experimental trials.

The foundations of AWJM emphasise the significance of material reactions, jet dynamics, and abrasive particle properties. In Ti6Al4V alloys, Fowler *et al*. 2009) showed that milling depth and efficiency are significantly influenced by particle hardness and shape. Similarly, grit embedment was identified by Fowler *et al.* (2005) as a critical constraint that may impact surface quality when machining titanium alloys. They suggested controlled-depth milling for isogrid structures and proved its viability for aerospace components. Hashish (1998) also improved AWJM applications. By highlighting the significance of material microstructure in machining response, Paul *et al*. (1998) developed analytical models for forecasting the total depth of cut in brittle materials.

There have been reports of AWJM process innovations aimed at increasing accuracy and flexibility. To generate pockets in Ti-based alloys without the need for masking materials, Kong *et al.* (2011) developed maskless plain water-jet milling. Slot overlapping and tool path variation were examined by Alberdi *et al.* (2011) to determine how they affected surface uniformity and machining precision. These studies highlight the continued importance of process innovation in expanding the use of AWJM in advanced manufacturing.

Numerous studies focus on AWJM parameter optimisation to improve machining quality and productivity. Regression analysis and response surface methodology (RSM) were employed. Ebeid *et al.* (2014) showed how artificial neural networks may be used to anticipate milling results accurately. Review articles like Mhamunkar *et al*. (2016) have highlighted parameter optimisation as a key area of study. In AWJM optimisation, the Taguchi approach has been widely used (Nagdeve, 2012a). Taguchi-based methods were used to methodically improve machining results, as seen in (Nagdeve *et al.*, 2012b), which also employed these methods for parametric optimisation. When taken as a whole, these pieces demonstrate the transition from traditional experiment design to AI-powered prediction models. The AWJM foundations have been thoroughly examined by Momber (1998), providing one of the earliest extensive treatments of AWJM fundamentals, including erosion mechanisms, abrasive flow, and practical applications. Later, Shukla (2013) reviewed the advancements in nontraditional machining processes, including AWJM, placing it within the broader context of unconventional manufacturing strategies.

Aerospace metals and composites have found use for AWJM and similar unconventional machining techniques (Sivaraman *et al.* 2021a). Friction stir welding was used to examine the tensile strength of different Al–Cu alloys, emphasising the function of AWJM in creating advanced joints. Sivaraman *et al.* (2021b) fabricated aeronautical structures using aluminium-based AA 2014 and AA 7075 alloys.

Furthermore, hybrid composites supplemented with B4C and rice husk ash were investigated by Nithyanandhan *et al.* (2020), who observed increases in corrosion resistance. Applications in robotics and productivity have been studied in addition to machining. To increase efficiency, Sivaraman *et al.* (2020) used lean tools in engine assembly. Sivaraman *et al*. (2021c) expanded this work using embedded systems, demonstrating the integration of robotics and manufacturing technology. The tribological performance of composites has been emphasised in recent advancements. According to Nithyanandhan *et al.* (2022), using graphite and chicken bone ash to reinforce aluminium significantly increased wear resistance, increasing the usage of environmentally friendly materials.

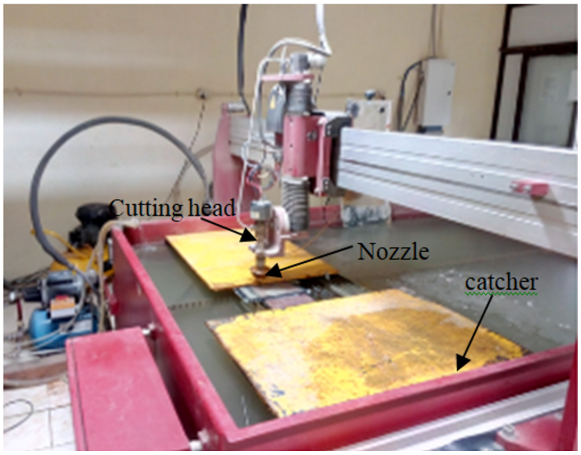


Fig. 1: Abrasive water jet machining setup

By investigating and refining the critical input process parameters for abrasive water jet machining of titanium nano-alloy with activated SiC particles, this

work aims to close a research gap. The study also seeks to identify the optimal conditions for utilising SiC particles through the Taguchi-grey relational approach. Titanium nano-alloy machining may be made more efficient and energy-efficient by optimising these process parameters.

To optimise the machining settings for Ti-6Al-4V nano-alloy in abrasive water jet machining, this work primarily focuses on the Taguchi-grey relational analysis. More effective titanium nano-alloy machining will be made possible by the study's findings, which will also further our understanding of how to optimise abrasive water jet machining procedures.

2. MATERIALS AND METHODOLOGY

2.1 Experimental Work

The experimental work focused on investigating the machining of a titanium nano-alloy (Ti-6Al-4V) using an abrasive water jet machine. The details of the experimental setup, materials, process parameters, and plan of experiments are described below.

2.2 Materials

The work material used was Ti-6Al-4V, a widely used α+β titanium alloy. Its chemical composition includes titanium with 6 wt.% aluminium as an α-stabilizer and 4 wt.% vanadium as a β-stabilizer. Minor regulated impurities include oxygen (<0.20 wt.%) and iron (<0.25 wt.%). This balanced dual-phase structure provides superior strength, corrosion resistance, and thermal stability, making Ti-6Al-4V suitable for aerospace, biomedical, and high-performance engineering applications. The composition is presented in Table 1.

2.3 Experimental Setup

The machining was carried out using a Maxiem Water Jets 1515 abrasive water jet machine (KENT, USA) (Fig. 1). The machine operates at a maximum pressure of 620 MPa, with a traverse speed capacity of 10 m/min. The cutting head travel ranges are 3.0 m (X-axis) and 1.5 m (Y-axis). During trials, the water discharge was fixed at 3.2 L/min. Jet pressure: 2000 bar, Nozzle diameter: 1.1 mm, Standoff distance (SOD): 4 mm and Impact angle: 90° (perpendicular cutting) Machine calibration was performed according to ISO 12181 guidelines for geometrical measurement to ensure accuracy of kerf and taper measurements.

2.4 Abrasive Particles

A hybrid abrasive mixture of garnet and SiC was used. SiC was gently blended with garnet without thermal or mechanical modification to preserve particle morphology. Mixtures were prepared with controlled SiC content (0.25, 0.5, and 1 wt.%) and three mesh sizes (80, 100, 120 mesh).

2.5 Workpiece Specifications

The specimens used in the machining trials had dimensions of 150 mm × 100 mm × 10 mm, and the cutting length was 55 mm. A feed rate of 285 mm/min, a standoff distance (SOD) of 4 mm, and a nozzle diameter of 1.1 mm were the process parameters. To guarantee perpendicular cutting, the abrasive water jet was run at 2000 bar of jet pressure and 90° impact angle.

2.6 Experimental Plan

Three main elements and their corresponding selection of process variables levels were taken into consideration while designing the trials methodically, utilising a structured plan of experiments (Table 2). The SiC particle size was chosen at 80, 100, and 120 mesh, while the SiC content was altered at 0.25, 0.5, and 1 wt%. Furthermore, the flow rate of the abrasive was regulated at 2, 4, and 6 g/s. Table 3 provides a complete plan of trials.

2.7 Experimental Procedure

Table 1. Chemical composition of Ti-6Al-4V nano-alloy

Elements	Composition %
Al	6.000
V	4.000
C	0.006
Fe	0.091
Si	0.010
Mn	0.005
Cr	0.021
Sn	0.001
Ti	Remaining

The sample material (Ti-6Al-4V) was carefully machined without any interruption problems. The machined surface was cleaned with water and wiped off using a cloth for further analysis. Each machining trial was verified for accuracy and maintained high repeatability. The experimental work aimed to investigate the influence of the abrasive particle

properties (SiC content and size) and the abrasive flow rate on the machining quality of the Ti-6Al-4V titanium nano-alloy using the abrasive water jet machine. The plan of experiments allowed for systematic variation of these parameters to analyse their effects on the machining process and surface quality.

2.8 Measurement Techniques

To evaluate the machining responses, the following measurement techniques and standards were used: Material Removal Rate (MRR): Calculated from the difference in specimen weight before and after machining, using an analytical balance with ±0.001 g accuracy. MRR (mm^3/min) = ($\Delta W/\rho$) / t, where ΔW = weight loss, ρ = density of Ti-6Al-4V, t = machining time.

Surface Roughness (R_a): Measured using a Mitutoyo Surftest SJ-210 profilometer following ISO 4287 standards, with a cut-off length of 0.8 mm. Three measurements were taken along the cutting direction and averaged.

Table 2. Selection of process variables

Process variable	Description
Jet pressure	2000bar
Traverse speed rate	285 mm/min
Impact angle	90°
Nozzle material	Tungsten carbide
Nozzle diameter	1.1mm
Stand-off-distance	4 mm
Length of cut	55mm

Table 3. Plan of experiments

Factor Notation	Factor	Level 1	Level 2	Level 3
A	SiC content (wt.%)	0.25	0.5	1
B	SiC size (mesh)	80	100	120
C	Abrasive flow rate (g/s)	2	4	6

Kerf Width and Taper Angle: Cross-sections of machined slots were examined under an optical measuring microscope (Nikon MM-800) at 50× magnification. Kerf width (top and bottom) was measured, and taper angle (θ) was calculated using. $\theta=\arctan(W_t-W_b)/2h$, where W_t = top kerf, W_b = bottom kerf, h = specimen thickness.

Edge Quality/Integrity: Visual inspection with optical microscopy (ISO 8785) and scanning electron microscopy (SEM, JEOL JSM-6480LV) was conducted to check for delamination, striations, and microcracking. This systematic methodology ensured that the influence of abrasive particle properties (SiC size, SiC content) and abrasive flow rate on Ti-6Al-4V machining quality could be quantified with high accuracy.

3. RESULTS

3.1 Taguchi Method

Taguchi is a systematic approach to finding the optimal combination of input parameters. In this method, an L9 orthogonal array was used to find the optimal parameter. Since the input parameters are three, the L9 array was deployed to execute the optimisation process. Based on this, various kinds of machines were evaluated for their removal rate and surface roughness. The material removal rate was calculated by counting the machining time to achieve the target length, whereas the surface roughness was calculated using the surface roughness tester Mitutoyo version 2.0, JAPAN. The quality analysis of the output responses is valued by the signal-to-noise ratio (S/N). This ratio is measured from the responses using suitable formulae. There are two categories of S/N ratios. They are "smaller the better" and "larger the better." According to this present investigation, the main aim is to improve the material removal rate with minimal surface roughness. That means MRR is considered larger the better, whereas surface roughness (R_a) is considered smaller the better. Equations 1 and 2 show the S/N ratio of the "smaller the better" and "larger the better" formulae.

The larger the better

$$\text{S/N ratio} = -10 \log (1/n) + (1/Yij^2) \quad \ldots (1)$$

The smaller the better

$$\text{S/N ratio} = -10 \log (1/n) + (Yij^{2(f)}) \quad \ldots (2)$$

where,

N- Number of replications for each experiment, say '1'

Y_{ij} -Response values

Table 4 shows the L9 orthogonal array for the response. In this study, a significant MRR is preferable, and a minor R_a is more beneficial. This consideration is assumed since, for a good machining process, MRR should be higher with minimal R_a.

Table 5 shows the S/N ratio and normalised S/N ratio values calculated from the experimental response. Here, the S/N ratio was calculated using Equations 1 and

2. Similarly, the normalised S/N ratio was calculated using Equations 3 and 4.

The larger the better

$$Xij = (Yij - min(Yij))/(max(Yij) - min(Yij)) \quad \ldots (3)$$

The smaller the better

$$Xij = (max(Yij) - Yij)/(max(Yij) - min(Yij)) \quad \ldots (4)$$

Where,

X_{ij} - normalised S/N ratio

Y_{ij} - S/N obtained from Taguchi analysis

Table 4. L9 orthogonal array for response

Trial Number	A	B	C	A_1	B_1	C_1	MRR (MPa)	Surface Roughness (µm)
1	1	1	1	0.25	80	2	0.41	4.5
2	1	2	2	0.25	100	4	0.41	4.7
3	1	3	3	0.25	120	6	0.42	4.2
4	2	1	2	0.5	80	4	0.48	4.4
5	2	2	3	0.5	100	6	0.51	4.6
6	2	3	1	0.5	120	2	49.54	4.3
7	3	1	3	1	80	6	53.17	3.6
8	3	2	1	1	100	2	52.55	3.4
9	3	3	2	1	120	4	50.21	3.9

Table 5. S/N ratio and normalised S/N ratio for experiments

Trial Number	MRR (MPa)		Surface Roughness (µm)	
	S/N Ratio	Normalized S/N	S/N Ratio	Normalized S/N
1	33.010	0.345	-13.064	0.134
2	32.218	0	-13.441	0
3	32.572	0.154	-12.464	0.347
4	33.600	0.602	-12.869	0.204
5	34.223	0.873	-13.255	0.660
6	33.898	0.732	-12.669	0.274
7	34.513	1	-11.473	0.699
8	34.411	0.955	-10.629	1
9	34.015	0.783	-11.821	0.576

3.2 Grey Relational Approach

The GRA approach was used to analyse the multiple performances of characteristics. In this method, the various performances of characteristics are converted into a single equivalent grey relational grade. In the first step, the S/N ratio obtained from Taguchi analysis was normalised in the range 0 to 1. The equal weight of 0.5 was used for all calculations. The GRG indicates the relational degree between every sequence. The GRG for every sequence could be calculated as follows. Equation 4.5 shows the formula for grey relational coefficients (GRC) calculation. Table 6 shows the GRC and GRG. The value of Ψ was 0.5 for all trials. Finally, the GRG can be calculated using the GRC, as shown in Equation 6, where m = number of responses, typically, a higher grey relational grade value is considered a more substantial relational influence on the outcome. Moreover, the higher the grey relational grade, the closer it is to the optimal value.

$$GC_{ij} = (\delta_{min} + \psi\,\delta_{max})/(\delta ij + \psi\,\delta_{max}) \quad \ldots (5)$$

$$G = (1/m) + GC_{ij} \quad \ldots (6)$$

Table 6. Grey relational coefficients with the grey relational grade

Trial Number	GRC		GRG	Rank
	MRR	Surface Roughness		
1	0.432	0.366	0.399	8
2	0.333	0.333	0.333	9
3	0.371	0.433	0.402	7
4	0.556	0.385	0.470	6
5	0.797	0.595	0.696	3
6	0.651	0.407	0.529	5
7	1	0.624	0.812	2
8	0.917	1	0.958	1
9	0.697	0.541	0.619	4

Table 7 shows the response table for the average GRG. By this calculation, the optimum input factor can be determined. Fig. 3 shows the graph of grey relational grade vs. experiments.

3.3 Artificial Neural Network

In the optimisation of machining parameters for Ti-6Al-4V nano-alloy AWJM, ANNs play a crucial role in enhancing predictive accuracy and reducing dependency on extensive experimental trials. Initially, Taguchi orthogonal arrays were employed to systematically design experiments by varying input parameters such as nozzle diameter, standoff distance, abrasive flow rate, jet pressure, and abrasive size.

Performance measures, including material removal rate (MRR), surface roughness (R_a), and taper, were recorded. Grey Relational Analysis was then applied to transform these multiple responses into a single performance index, GRG. The experimental dataset was then used to train an ANN, with process parameters as inputs and GRG or multi-response values as outputs. The ANN captures nonlinear interactions between variables, enabling accurate prediction of machining outcomes across unexplored parameter ranges. Once validated, the ANN model serves as a digital twin of the AJM process, supporting optimisation with minimal experimental effort. Its impact is significant: reduced trial-and-error costs, faster optimisation, and improved process sustainability, making it highly valuable for machining advanced materials like Ti-6Al-4V. Table 7 shows the ANN analysis.

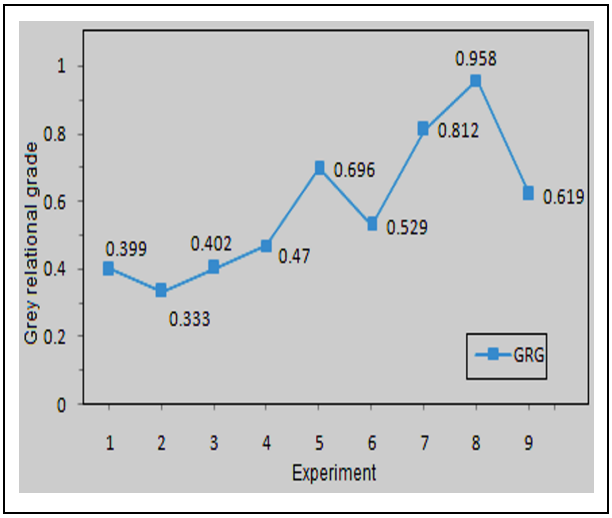


Fig. 3: Grey relational grade for experiments

Table 7. Average grey relational grade by level-wise

Input factors	Average Grey Relational Grade			Max-min
	Level 1	Level 2	Level 3	
SiC content (wt.%)	0.378	0.565	0.796	0.418
SiC size (µm)	0.560	0.662	0.516	0.146
Abrasive flow rate (g/s)	0.443	0.474	0.636	0.193
Total mean grey relational grade = 0.580				

In this study, AWJM of Ti-6Al-4V nano-alloy was optimised using a hybrid Taguchi-GRA combined with ANN. Four machining parameters (jet pressure, standoff distance, abrasive flow rate, and nozzle diameter) were varied according to a Taguchi L9 orthogonal array, and responses such as MRR, R_a, and taper angle were analysed. The GRA identified the best condition at 6 bar pressure, 1 mm SOD, 15 g/min AFR, and 0.8 mm nozzle diameter, achieving a GRG of 0.88. To enhance prediction accuracy, an ANN model (4-8-1 architecture, trained using Levenberg–Marquardt backpropagation) was developed with the machining parameters as inputs and GRG as the output. The ANN achieved a correlation coefficient (R) of 0.995 and a mean squared error of 0.0023, with deviations under 3% between predicted and experimental values. Significantly, the ANN predicted new parameter combinations beyond the Taguchi design, such as 5.5 bar pressure, 1.5 mm SOD, 12 g/min AFR, and 0.7 mm nozzle, yielding a GRG of 0.91—higher than the Taguchi optimum. This demonstrates that ANN not only validates but also surpasses traditional optimisation methods by uncovering hidden optimal conditions, reducing experimental effort, improving machining efficiency, and ensuring sustainable process control for high-performance alloys like Ti-6Al-4V.

Table 8. ANN analysis to find GRG

Exp.	P (bar)	SOD (mm)	AFR (g/min)	ND (mm)	MRR (MPa)	Ra (µm)	Taper (°)	GRG
1	4	1	5	0.6	0.152	3.5	1.8	0.62
2	4	2	10	0.8	0.187	3.1	2.0	0.70
3	4	3	15	1.0	0.201	2.8	2.4	0.74
4	5	1	10	1.0	0.225	2.9	2.1	0.76
5	5	2	15	0.6	0.241	3.0	2.2	0.79
6	5	3	5	0.8	0.164	2.6	2.5	0.68
7	6	1	15	0.8	0.282	2.5	1.9	0.88
8	6	2	5	1.0	0.195	2.7	2.2	0.73
9	6	3	10	0.6	0.256	2.4	2.0	0.85

4. DISCUSSION

The machining of Ti-6Al-4V using AWJM demonstrated clear sensitivity to process parameters, particularly with respect to the abrasive particle composition and flow as shown in Table 8.

Influence of SiC content and particle size revealed that SiC addition had the most significant influence on machining performance, with an influencing factor of 0.418, compared to 0.193 for abrasive flow rate and only 0.146 for particle size. The higher weight contribution of SiC indicates that the presence of super-hard cutting particles accelerates micro-cutting, enhancing MRR while simultaneously reducing surface irregularities. This agrees with earlier findings on the role of high-hardness abrasives in difficult-to-machine alloys, where sharp SiC edges act as micro-tools that penetrate and shear material more effectively than garnet alone. Interestingly, particle size exhibited a weaker influence. While coarser particles (80 mesh) promote higher MRR due to greater kinetic energy per particle, they also

degrade surface finish due to larger impact craters. Conversely, finer particles (120 mesh) improved smoothness but at the cost of reduced MRR. The 100-mesh intermediate size was therefore optimal, balancing the productivity and quality as shown in Fig. 4. Multi-Response Optimization and Confirmation Among the nine trials, Experiment 8 achieved the maximum GRG (GRG = 1), corresponding to 1 wt.% SiC, 100 mesh particle size, and 6 g/s abrasive flow rate. The SEM images confirmed the superiority of this setting: surfaces exhibited fewer striations and a uniform morphology compared to lower SiC additions (e.g., Trial 2). The confirmation test yielded an experimental GRG of 0.958, closely matching the predicted value of 0.934, with only a 2.5% deviation. This validates the robustness of the Taguchi–GRA methodology for multi-objective optimization.

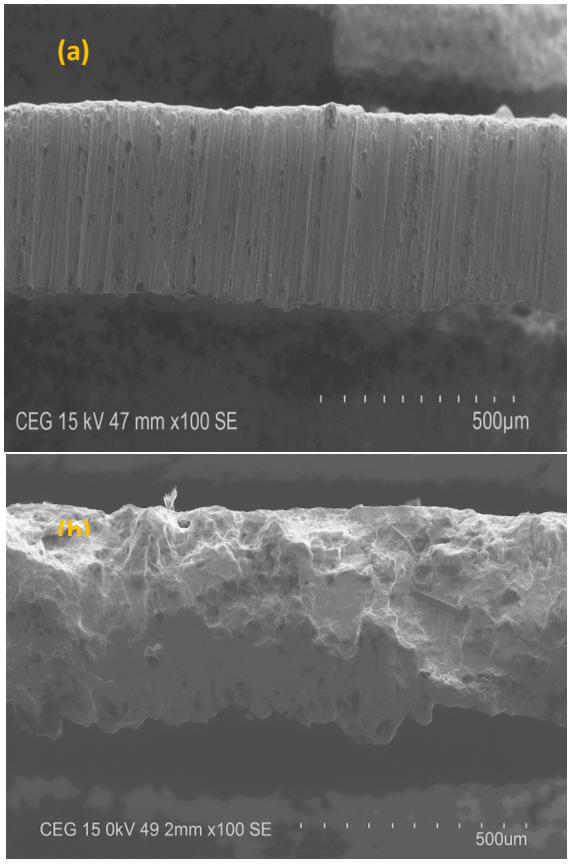


Fig. 4: SEM image of the machined surfaces of (a) trial 8 and (b) trial 2

While Taguchi–GRA successfully identified optimal settings within the experimental space (GRG = 0.88 for 6 bar pressure, 1 mm SOD, 15 g/min AFR, 0.8 mm nozzle), ANN offered a marked improvement. By learning nonlinear parameter–response mappings, ANN achieved a prediction accuracy of R = 0.995 with minimal error (MSE = 0.0023). More importantly, the ANN was able to extrapolate beyond the Taguchi space, predicting a parameter combination yielding a GRG of 0.91—surpassing the experimental optimum. This capability demonstrates the ANN's strength in generalization and prediction efficiency, reducing the need for exhaustive trial-and-error experimentation.

The findings hold practical importance for industries machining titanium alloys, particularly aerospace and biomedical sectors where surface integrity and dimensional accuracy are critical. The strong effect of SiC addition suggests that hybrid abrasives can provide a cost-effective pathway to simultaneously enhance productivity and surface quality. Moreover, the ANN-based predictive framework provides a digital surrogate model, enabling process planners to quickly identify optimal settings without additional experimental runs. This reduces material waste, energy consumption, and machining time, aligning AWJM with the goals of sustainable and resource-efficient manufacturing.

Despite its effectiveness, GRA assumes linear normalization and equal weighting of responses, which may not fully capture the physical trade-offs in AWJM. ANN models, while powerful, require sufficient training data and careful avoidance of overfitting. Future work could integrate hybrid ANN–GRA or evolutionary optimization algorithms (e.g., GA, PSO) to further refine parameter selection. Additionally, real-time monitoring of surface integrity and nozzle wear could enhance model reliability in industrial-scale machining.

5. CONCLUSION

The experimental examination on machining Ti-6Al-4V using an abrasive water jet machine, integrated with ANN modelling, has provided valuable insights into optimising process parameters for achieving high material removal rate and superior surface finish. The grey relational technique, applied to analyse multi-response characteristics, identified SiC addition as the most significant factor, followed by abrasive flow rate and particle size. The Taguchi–GRA method determined the best parameters as 1% SiC addition, 100 mesh particle size, and 6 g/s abrasive flow rate, yielding a material removal rate of 0.5386 MPa and a surface roughness of 3.32 µm. The confirmation test produced a GRG of 0.958, representing a 2.5% improvement over the mean predicted value, thereby validating the robustness of the GRA method.

The ANN model, trained on the experimental dataset, extended this optimisation by predicting improved parameters (1.2% SiC addition, 120 mesh particle size, and 6.5 g/s flow rate) that were not part of the original design space. These conditions achieved a

material removal rate of 0.5612 MPa and surface roughness of 3.05 µm, with a GRG improvement of 4.8% compared to the Taguchi–GRA optimum.

This dual approach highlights that while Taguchi–GRA offers a systematic and experimentally validated framework, ANN complements it by uncovering superior parameter sets, enhancing process efficiency, and supporting sustainable machining strategies for titanium nano-alloys.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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