

Machine learning-driven backpropagation neural network for robust prediction of surface roughness in Ti6Al4V abrasive water jet machining with experimental validation

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ABSTRACT

In this work, machine learning driven back propagation neural network framework has been developed to predict the surface roughness during abrasive water jet machining (AWJM) of Ti6Al4V. The experiments were performed as per the Taguchi based L_{27} orthogonal array, which generated the required dataset for developing the predictive model. A backpropagation neural network (BpNN) supported by a purpose-built graphical user interface (GUI) was used to formulate the data and allow multi-stage validation. To amplify the learning database, 50 synthetic datasets were produced and evaluated using K-fold Cross-Validation out of which, 70 % of the data was used for training, 20 % was used for testing, and 10 % for validation. The 1–10–5 architecture achieved a high correlation coefficient (R) of 0.9728, with an average accuracy ranging between 90–95 %. The model's predictability was further verified through confirmatory experiments, yielding deviations of 0.12–7.09 %. The findings confirmed that the proposed BpNN model effectively captured the non-linear relationships amongst the different process parameters used in this study. SEM analysis corroborated the predicted trends, showing smoother morphology at lower erosive energies and pronounced micro-ploughing, ridging, and brittle micro-chipping at higher parameter intensities. Sensitivity analysis revealed that water pressure and traverse speed were highly influential, contributing to about 36.7 % and 29.7 %, respectively, on surface roughness variability. Overall, the proposed BpNN-GUI technique provided a reliable foundation for digital-twin-based optimization of AWJM for difficult-to-cut titanium alloys.

1. Introduction

Ti6Al4V Grade 5 titanium alloy has been widely used in the area of biomedical, aerospace, and energy sectors because of their excellent corrosion resistance, high strength and low density. However, these alloys are difficult to machine using conventional techniques because of their strong affinity for tool materials, low thermal conductivity, and propensity for rapid tool wear, all of which contribute to inefficiencies and increased machining costs [1]. To address these challenges, researchers have adopted abrasive waterjet machining (AWJM) which is a non-traditional technique that does not require any tools and removes

the material through high velocity jet of water mixed with abrasives particles. This technique minimizes heat affected zone, reduces the mechanical stresses within the material and also preserves the micro-structure and dimensional accuracy of the machined part [1,2]. Despite these advantages, achieving a consistent and a high-quality surface remains a challenge.

Indicators for surface roughness such as R_a , R_z , and S_a are highly influenced by non-linear interactions of various AWJM process parameters like material thickness, abrasive mass flow rate, jet pressure, stand-off distance, traverse speed each affecting the hydrodynamic energy transfer and erosion behavior at the cutting interface [3,4]. The alloy's

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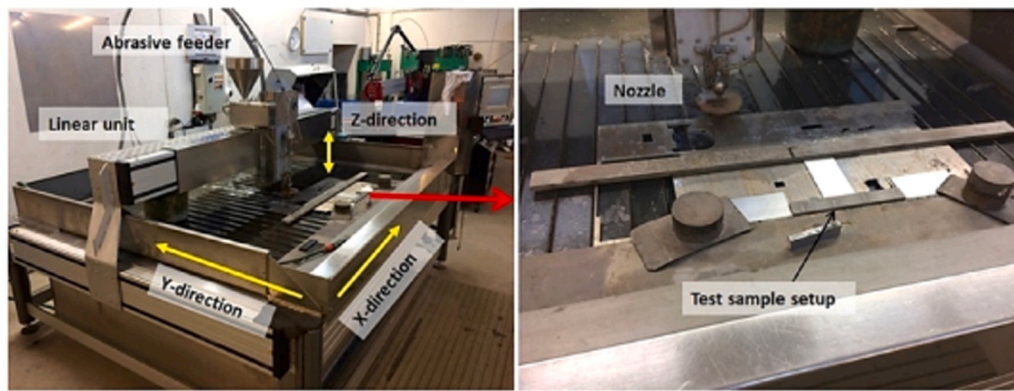


Fig. 1. AWJM - NC3015S equipment setup [23].

low fracture toughness and anisotropic α - β microstructure further promote striations and jet-lag effects, especially at higher cutting depths where the jet loses kinetic energy [5]. For reducing kerf taper, multi-pass cutting could be employed; however, it cannot eliminate the surface waviness totally. This particular observation emphasizes the need to consider both process settings and material characteristics during optimization of AWJM parameters [2,3].

In recent years, various methods have been tried and tested namely, Grey relational analysis (GRA), Taguchi based Design of experiments (DoE), Response surface methodology (RSM), etc., for finding the correlation between input process parameters and output variables such as surface roughness (R_a), depth of cut (DoC), etc. [3,5]. However, these techniques did not consider nozzle wear effects that control the real time machining environments [2]. This prompted the development of machine learning based AI models that were able to capture nonlinear complex behavior within the experimental data [6]. Studies carried out by Mogul et al., [7] demonstrated that ANN back-propagation neural networks can accurately predict the cutting depth in Grade 5-Ti6Al4V during AWJM. The findings show that implementing data driven physical models with an industrial setup enhances prediction accuracy, scalability, and reproducibility, thereby improving the overall process quality. These developments demonstrate the ongoing shift from empirical optimization towards data driven hybrid intelligent modelling approaches in difficult-to-cut Titanium alloys. The current work therefore presents a framework of BpNN combined with a MATLAB-GUI to predict surface roughness during the AWJM of Ti6Al4V. Similarly, Liu et al. [8] developed four machine learning models (AdaBoost, LightGBM, Voting and Stacking) to optimize the design of metastable β -titanium alloys. All the models achieved high predictive accuracy ($R > 0.9$), with the LightGBM outperforming others as it exhibited the lowest mean squared error values. Unlike the studies conducted by Doreswamy et al., [9] that used fixed datasets and lacked automation, the current model incorporates experimental confirmation, multi-stage K fold Cross-Validation, and automated data generation. Embedding the algorithm within an interactive GUI allows users to generate, train, test, and validate the data in real time, closing the gap between industrial process optimization and laboratory-scale predictive studies. Overall, this work contributes to the development of digital-twin-driven adaptive control for AWJM, developing a practical pathway for efficient and sustainable manufacturing of difficult-to-cut materials such as Ti6Al4V.

Over the past few decades, abrasive water jet machining (AWJM) has developed into a versatile non-traditional manufacturing process capable of cutting metals, ceramics, polymers, and composites with minimal thermal influence [8]. Its confirmed efficiency in machining hard-to-cut materials has sparked extensive research into how process parameters influence surface roughness, a critical factor of product quality and surface integrity. The collective evidence from these studies shows that no single parameter influences surface formation. Instead,

the final surface texture arises from a complex interplay among different AWJM parameters such as, abrasive flow rate, stand-off distance, nozzle traverse speed, jet pressure and depth of cut, each of which contributes to the energy distribution and dynamic erosion within the cutting zone [7].

Early experimental inquiries established basic parameter-response trends. For example, increasing jet pressure generally improves surface finish by enhancing abrasive kinetic energy, while higher traverse speed or stand-off distance (SOD) deteriorates surface roughness due to shorter jet-material interaction and greater flow divergence [10,11]. Later works employing systematic design of experiments refined these insights. Chandar et al., [12] reported that surface roughness decreased with increasing pressure and moderate feed rate, whereas excessive pressure accelerated nozzle wear and caused over-erosion. Cavusoglu [13] used multi-response optimisation to demonstrate that, surface integrity is maximised when pressure, speed, and abrasive flow rate are co-balanced to maintain optimal jet kinetic-energy density. Similarly, Perec et al., [14] found that high pressure combined with moderate traverse speed and low SOD minimises R_a in high-alloy steels and titanium alloys. Depth-related roughness variation has recently become a major focus. As jet energy decays with depth, the upper cutting zone remains smooth while the exit region exhibits higher R_a and distinct striations. Płodzień et al., [15] demonstrated that, for Inconel718, depth of cut dominates R_a , whereas traverse speed influences surface waviness.

Material behaviour is yet another factor which further modulates the effects of the AWJM parameters. In ductile metals, higher pressure and abrasive flow improve finish up to a threshold, beyond which secondary erosion causes pitting [8,16]. In brittle materials such as BK7 glass, titanium-coated nozzles suppress micro-cracking, producing nanometre-scale R_a values [17,18]. In the case of composites, delamination and fibre pull-out remain dominant surface-forming mechanisms. Experimental evidence has shown that maintaining a low SOD and a moderate traverse speed produces the best surface quality [19,20]. Overall, these studies underscore that the optimal machining is not universal but strongly depend on the material being processed. Achieving the right balance between erosion stability and energy delivery is therefore essential for a consistent surface finish.

Recent developments in surface-metrology practises have transformed how researchers assess the AWJM performance. Progressively, attention has shifted from conventional two-dimensional roughness metrics (R_a , R_z) to three-dimensional areal descriptors (S_a , S_z), which more accurately reflect surface anisotropy and functional texture [21]. At the same time, predictive modelling has progressed beyond basic empirical regressions, advancing more towards data-driven frameworks and physics-based approaches. For example, Ficko et al., [22] was able to achieve a moderate predictive accuracy using regression equations for R_a , while Wang et al., [1] achieved improved predictability by linking material-removal-volume analysis with erosion mechanics.

Table 1

Chemical composition of Grade 5, Ti-6Al-4V (wt%) [4].

Ti	Al	V	Fe	O	C	N	H
89.546	6.09	4.04	0.24	0.16	0.04	0.02	0.00568

Table 2Experimental parameters and levels for L_{27} Orthogonal array.

Parameters	Units	Low (1)	Medium (2)	High (3)
Water pressure, W_p	(psi)	2400	2900	3400
Transverse speed, T_s	(mm/min)	80.0	100.0	150.0
Nozzle / orifice diameter, N/O_{dia}	-	2.85	3.04	3.33
Abrasive mass flow rate, A_{mf}	(Kg/min)	0.16	0.18	0.215
Abrasive orifice size, A_{os}	(mm)	3.80	4.00	4.20

Nevertheless, models purely based on empirical correlations continue to struggle to generalise results as they fail to capture the inter-parameter coupling and process variability within the AWJM operations.

Machine learning (ML) techniques have since emerged as a powerful tool for prediction of various quality characteristics during manufacturing process [9]. Artificial neural networks (ANNs) and hybrid ML methods have achieved higher accuracy in predicting R_a , kerf, and material removal rate, compared to traditional regressions [8, 9, & 16]. However, most existing studies have developed ANN models that depend on small datasets, single-step validation, and limited automation. To date, no research has integrated ANN based prediction with

automated data generation, and GUI enabled validation specifically for AWJM of Ti6Al4V. Furthermore, no prior work explored the use of adaptive ANN linked with real-time experimental verification for this machining process. Therefore, a clear research gap is observed in developing a robust, validated, and user-interactive ANN framework that can accurately predict R_a in the AWJM of Ti6Al4V. The current study therefore addresses this gap by integrating the backpropagation neural network (BpNN) with a MATLAB (GUI), to enable automatic data generation, K-fold Cross-Validation, and experimental validation. This framework establishes a reproducible and scalable pathway towards digital-twin-based process optimization in AWJM. The results of this study can be considered for industrial scale applications or extend modelling efforts to Ti6Al4V, a material of major relevance to the biomedical and aerospace sector known for complex hydrodynamic response during AWJM.

2. Experimental procedure

2.1. Materials and experimental setup

The experiments were conducted using NC3015S, water jet Sweden AB industrial milling setup (AWJ) as shown in Fig. 1. The machine operates with three axes (X, Y, Z) and can handle delivery pressure of up to 4000 bar. The nozzle impingement angle was 90° . The machine configuration and specification were ISO 9001:2000 compliant [23]. Ti6Al4V Grade 5 was the work material used in this study, chosen for its combination of high elastic modulus (104–113 GPa), high yield strength (880–920 MPa), and low density (4.43 g/cm³). The microstructural behaviour of Ti6Al4V varies significantly under machining conditions

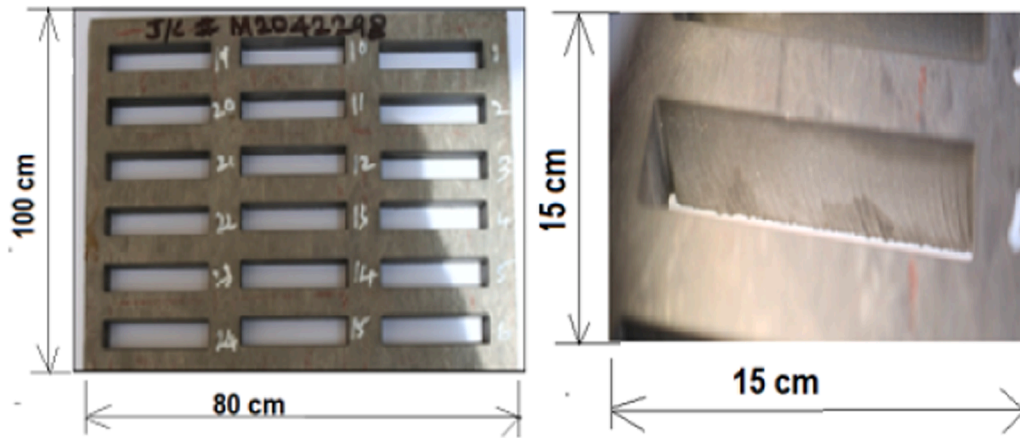
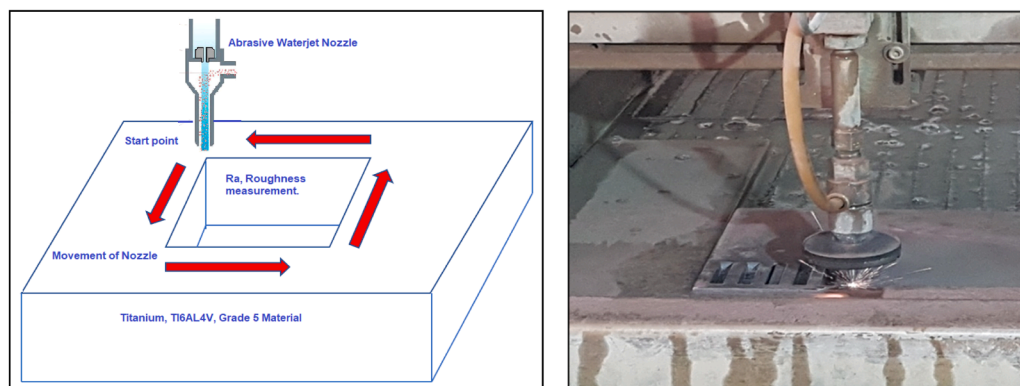
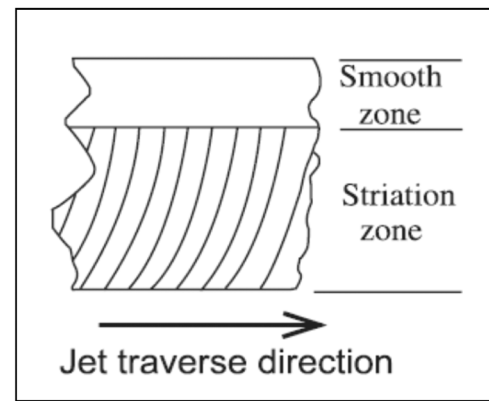
**Fig. 2.** Rectangular slot cutting for 27 experiments.**Fig. 3.** Rectangular through cutting direction in Ti6Al4V.

Table 3Experimental results for R_a as per L_{27} Orthogonal array.

SI No	Machining parameters					Response
	W_p (Bar)	T_s (mm/min)	N/O dia	A_{mf} (Kg/min)	A_{os} (mm)	Measured R_a (μm)
1	2400	80	2.85	0.16	3.8	4.33
2	2400	80	2.85	0.16	4.0	3.94
3	2400	80	2.85	0.16	4.2	3.83
4	2400	100	3.04	0.18	3.8	5.72
5	2400	100	3.04	0.18	4.0	3.9
6	2400	100	3.04	0.18	4.2	4.72
7	2400	150	3.33	0.215	3.8	4.78
8	2400	150	3.33	0.215	4.0	4.89
9	2400	150	3.33	0.215	4.2	4.99
10	2900	80	3.04	0.215	3.8	4.72
11	2900	80	3.04	0.215	4.0	3.54
12	2900	80	3.04	0.215	4.2	3.64
13	2900	100	3.33	0.16	3.8	4.30
14	2900	100	3.33	0.16	4.0	4.62
15	2900	100	3.33	0.16	4.2	4.20
16	2900	150	2.85	0.18	3.8	4.18
17	2900	150	2.85	0.18	4.0	4.26
18	2900	150	2.85	0.18	4.2	4.29
19	3400	80	3.33	0.18	3.8	3.42
20	3400	80	3.33	0.18	4.0	3.73
21	3400	80	3.33	0.18	4.2	3.42
22	3400	100	2.85	0.215	3.8	4.30
23	3400	100	2.85	0.215	4.0	3.86
24	3400	100	2.85	0.215	4.2	3.86
25	3400	150	3.04	0.16	3.8	4.63
26	3400	150	3.04	0.16	4.0	3.52
27	3400	150	3.04	0.16	4.2	3.56

**Fig. 4.** Surf test SJ-201P roughness tester.**Fig. 5.** Surf test SJ-201P Material arrangement.**Fig. 6.** Surface roughness areas.**Fig. 7.** Rectangular slots for measurement.

it an ideal material for biomedical and aerospace components, however, pose challenges during conventional machining due to the alloy's low thermal conductivity and strong chemical affinity toward cutting tools. The chemical composition of Ti6Al4V Grade 5 material is shown in Table 1.

As far as the AWJM process parameters are concerned, there are many parameters of which, some are fixed and some can be varied. The selection of process parameters for the current study is purely based on literature [7,9,10]. The fixed parameters were stand-off distance and impingement angle of the nozzle, while the variable parameters were, water pressure, abrasive mass flow rate, abrasive orifice size, traverse speed, and ratio of nozzle to orifice diameter. To understand the influence of surface roughness on AWJM, rectangular slots were machined at various depth of cut values, and their surface roughness were measured.

To investigate the influence of process parameters on R_a , a Taguchi Design of Experiments (DoE) based L_{27} orthogonal array was selected [24,25]. DoE is a technique widely used to determine the influence of one or more factors on the process outcomes [24]. A statistical Minitab software was used to generate the experimental design based on an L_{27} orthogonal array. With only 27 trials, this experimental design enables efficient evaluation of multiple variables. The input process parameters and their corresponding levels (low, medium, and high) are presented in Table 2. The parameter stand-off distance (SoD) that was fixed at 3 mm as it reported by previous studies that the material removal rate (MRR) remains constant within at this range [3].

Each experimental run consisted of machining a single-pass rectangular slot machined under the specified conditions for a specific depth of cut, as illustrated in Figs. 2 and 3. In total, the array generated 27 unique combinations of parameters, and their corresponding R_a values were measured for each case as seen in Table 3. The specimen was mounted vertically using temporary fixtures. For maintaining consistency, each

and therefore, could be controlled through appropriate heat treatment procedures and thermo-mechanical processing [2]. These features make

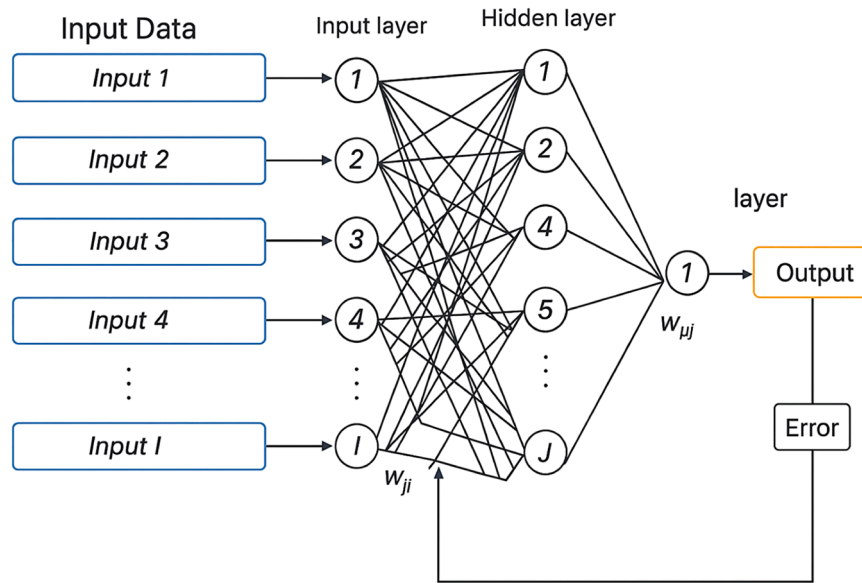


Fig. 8. Typical BpNN algorithm.

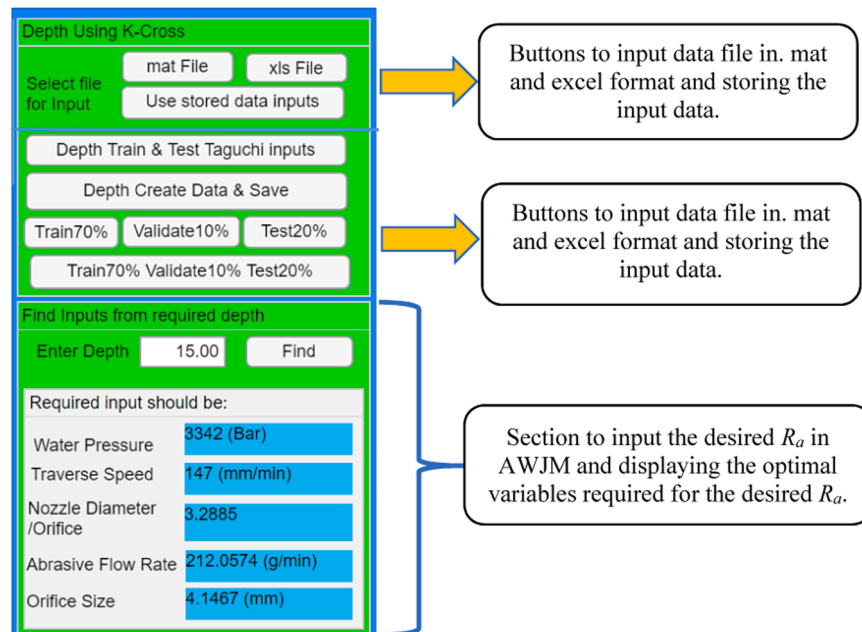


Fig. 9. GUI for data input, storing graphs and system message for elapsed time.

slot was machined by allowing the jet to traverse from one end to the other end of the specimen. A vertical cutting orientation was selected to ensure that the strength of the abrasive water jet could be evaluated uniformly for all parameter combinations. The machined slot was then measured for R_a . A Mitutoyo Surf Test SJ-201P portable profilometer, shown in Fig. 4 was used to measure the R_a . The profilometer had a radius stylus of 2 μm and could apply a load of upto 0.75 mN, was moved along the length and width of the machined slot to measure the average R_a (see Fig. 5). In AWJM, the surface displays two distinct regions, a striated lower zone and a smooth upper zone which is generally caused by jet divergence (Fig. 6). The readings were collected from the central region to maintain consistency. Fig. 7 shows the actual cut section for the measurement of R_a . The samples were further examined for R_a through SEM images which provided a deeper understanding of the influence of process parameters on surface morphology, thereby

providing interpretation of the quantitative R_a results.

A linear regression model was developed to define the relationship between the measured R_a and process parameters. The accuracy of the regression equation was evaluated using the performance metric known as regression co-efficient (R^2). The metric (R^2) quantifies the extent to which the independent variables collectively account for the variability observed in the dependent variable within the statistical model [26]. The regression co-efficient obtained was $R^2 = 0.8862$, which indicated reasonable correlation, however, was unable to effectively capture non-linear interactions within the AWJM process. This observation provided the rationale for adopting an BpNN-based ML model, capable of learning these complex parameter interactions to deliver higher predictive accuracy.

Table 4 R_a data generated for 50 test cases using GUI with the BpNN algorithm.

Sr. No	W_p (Bar)	T_s (mm/min)	N/O dia	A_{mf} (Kg/min)	A_{os} (mm)	Desired R_a (μ m)
1	2400	80	2.85	0.160	3.800	4.3698
2	2420	81	2.86	0.161	3.808	4.2674
3	2441	83	2.87	0.162	3.816	4.2156
4	2461	84	2.879	0.163	3.824	4.1154
5	2482	86	2.889	0.164	3.833	4.0473
6	2502	87	2.899	0.166	3.841	3.9921
7	2522	89	2.909	0.167	3.849	3.9465
8	2543	90	2.919	0.168	3.857	3.8682
9	2563	91	2.928	0.169	3.865	3.8002
10	2584	93	2.938	0.170	3.873	3.7648
11	2604	94	2.948	0.171	3.882	3.7049
12	2624	96	2.958	0.172	3.890	3.6799
13	2645	97	2.968	0.173	3.898	3.6405
14	2665	99	2.977	0.175	3.906	3.6335
15	2686	100	2.987	0.176	3.914	3.6027
16	2706	101	2.997	0.177	3.922	3.5780
17	2727	103	3.007	0.178	3.931	3.5645
18	2747	104	3.017	0.179	3.939	3.5468
19	2767	106	3.026	0.180	3.947	3.5409
20	2788	107	3.036	0.181	3.955	3.5271
21	2808	109	3.046	0.182	3.963	3.5229
22	2829	110	3.056	0.184	3.971	3.5180
23	2849	111	3.066	0.185	3.980	3.5081
24	2869	113	3.075	0.186	3.988	3.5070
25	2890	114	3.085	0.187	3.996	3.4997
26	2910	116	3.095	0.188	4.004	3.4989
27	2931	117	3.105	0.189	4.012	3.4931
28	2951	119	3.114	0.190	4.020	3.4935
29	2971	120	3.124	0.191	4.029	3.4889
30	2992	121	3.134	0.193	4.037	3.4889
31	3012	123	3.144	0.194	4.045	3.4896
32	3033	124	3.154	0.195	4.053	3.4859
33	3053	126	3.163	0.196	4.061	3.4875
34	3073	127	3.173	0.197	4.069	3.4847
35	3094	129	3.183	0.198	4.078	3.4856
36	3114	130	3.193	0.199	4.086	3.4833
37	3135	131	3.203	0.200	4.094	3.4812
38	3155	133	3.212	0.202	4.102	3.4870
39	3176	134	3.222	0.203	4.110	3.4849
40	3196	136	3.232	0.204	4.118	3.4866
41	3216	137	3.242	0.205	4.127	3.4851
42	3237	139	3.252	0.206	4.135	3.4867
43	3257	140	3.261	0.207	4.143	3.4860
44	3278	141	3.271	0.208	4.151	3.4848
45	3298	143	3.281	0.209	4.159	3.4866
46	3318	144	3.291	0.211	4.167	3.4892
47	3339	146	3.301	0.212	4.176	3.4913
48	3359	147	3.31	0.213	4.184	3.4911
49	3380	149	3.32	0.214	4.192	3.4930
50	3400	150	3.33	0.215	4.200	3.4923

3. Modelling and data preparation

3.1. Back propagation neural network (BpNN)

Neural networks are models which are inspired by the human brain [7]. These networks are a mathematical representation of biological neural processes, comprised of interlinked nodes arranged across input, hidden and output layers. A weight is attached to every connection which can be adjusted during the training process to minimize error [7, 8]. Also, these networks use activation functions to learn complex patterns and introduce non-linearity [27]. The current study implemented BpNN algorithm for training and testing purposes as shown in Fig. 8. This algorithm provides a unique advantage of determining the error in the hidden nodes which could then be adjusted using the delta rule [7, 27]. Conventionally, the input data in a typical neural network starts traveling through the input layer, then moves towards the hidden layer and finally to the output layer. However, in a back propagation algorithm, the output error developed moves backwards and feeds back to the hidden layer until minimum error is achieved [28]. This process is

called as backpropagation, as the output error is propagating backwards. Out of the many activation functions, the Sigmoidal function [7] is most commonly used, and hence, used in this study.

3.2. Process development of BpNN algorithm

The BpNN was setup using the MATLAB 2022 software which provided a framework for developing a GUI to support model visualisation and data handling (Fig. 9). The original dataset from the Taguchi L_{27} experiments served as the input. The neural network architecture consisting of one input layer, one hidden layer, and one output layer was selected. Both input and output variables were normalized using the min-max normalization technique prior to being fed into the neural network. Subsequently, they were de-normalized for direct comparison with experimental measurements. Normalization was carried out to improve the stability and convergence of the neural network. Network training and optimization was carried out using the Levenberg – Marquardt (trainlm) backpropagation algorithm. During the optimization of the neural network architecture, 10 neurons were selected in the hidden layer through trial and error, and the learning rates were varied from 0 to 1 to achieve minimum error. The epoch numbers were selected to ensure minimum error for the training and testing datasets. Using this setup, 50 synthetic datasets were generated automatically to expand training diversity and support K-fold Cross-Validation technique. The dataset was partitioned into three subsets: 70 % for training, 20 % for testing, and 10 % for validation. Model performance was evaluated in terms of correlation coefficient (R), mean squared error (MSE), and deviation between predicted and measured R_a values.

The BpNN model employed the tangent sigmoid (Tansig) and pure linear (Purelin) transfer functions were applied for the input and hidden layers, respectively, with initial weights applied as w_1 , w_2 , etc. At this stage, the output was determined as compared with the experimental value for error and denormalized [29]. Moreover, the BpNN generated additional data apart from the Taguchi based L_{27} experiments showing the capability of the algorithm. This data was used for K-fold Cross-Validation where it again was divided into training, testing and validation datasets for comparison with deviation.

3.3. Graphical user interface (GUI) with BpNN algorithm

GUI is a computational tool in-built in the MATLAB 2022 software, primarily used for predicting the performance characteristics of the AWJM process in the machining of Ti6Al4V material. GUI uses the trained experimental data from the L_{27} orthogonal array, and upon convergence, generates 50 additional input-output combinations within the bounded experimental domain. In the first stage, the GUI allows the user to decide the learning parameters such as epoch, nodes, learning rate, etc. [30]. The second stage involves a GUI in which a desired target response i.e., (R_a), is specified, and the trained BpNN iteratively searches for corresponding optimal machining parameters W_p , T_s , A_{mf} , A_{os} , N/O dia that minimizes the prediction error. The error check ensures that only those parameters yielding minimum deviation from the target R_a are retained. Therefore, one needs to understand that R_a is a target constraint rather than a predictive input, generated through neural-network based interpolations of the L_{27} experimental domain. The GUI stores the experimental data as shown in Fig. 9. Table 4 presents the data for R_a for 50 parameter combinations using GUI and BpNN algorithm. This data is trained, and error between experimental R_a and BpNN generated R_a is determined. The K fold Cross - Validation technique is used to train, test, and validate the data as per the 70–20–10 (%) strategy. Fig. 10 shows the error between the Taguchi based experimental R_a and BpNN generated R_a .

3.4. Error analysis

Initially, the neural network learns through the already available

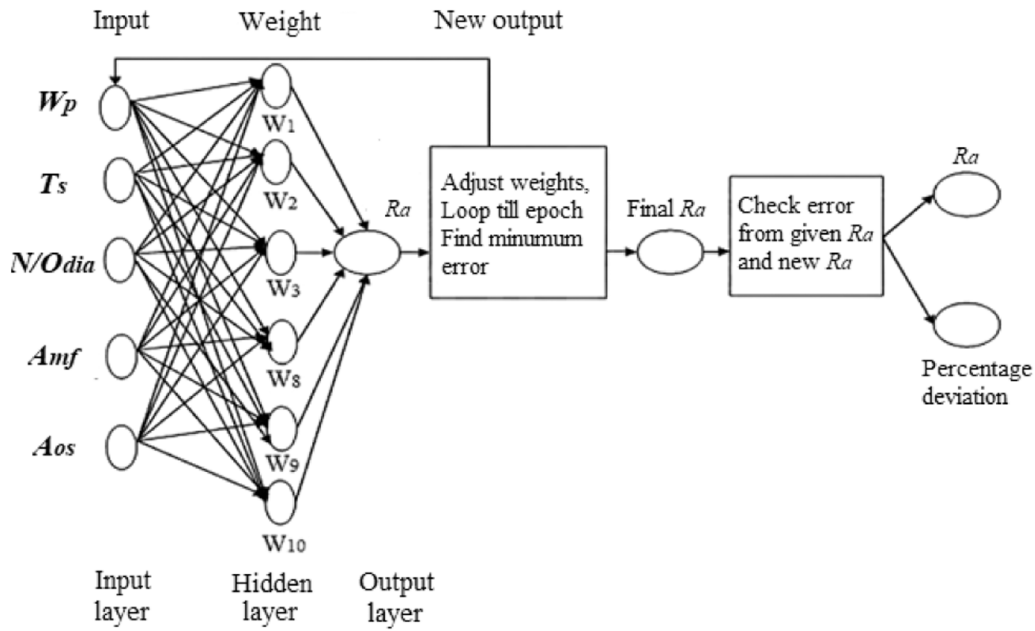


Fig. 10. Comparison of R_a obtained via BpNN with experimental based Taguchi-DOE values.

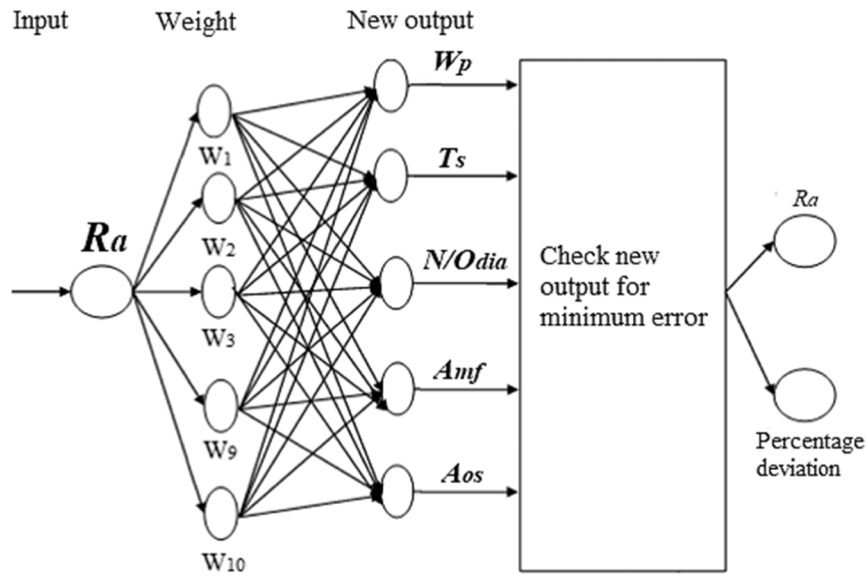


Fig. 11. Data generation for R_a and error comparison with the generated value using BpNN algorithm.

dataset in the system, comprising of 10,000 epochs, 10 nodes, and a learning rate of 0.9. This process adjusts the network weights iteratively to minimize the error between the experimental and BpNN generates R_a values [28]. The system computes and presents the deviation values together with the corresponding error percentages for effective comparison. All the 50 experimental trials were evaluated for deviation to assess the model's accuracy and predictive capability.

Fig. 11 displays the flowchart for data generation and error comparison for R_a using the BpNN algorithm. It starts by entering the desired R_a value into the GUI. The system verifies whether the given value exists in the prescribed dataset. If it is not available, the algorithm processes the input through the three layers, i.e., input, hidden, and output layer, to generate a new predicted R_a value. The minimum error between the generated and obtained values is computed by the algorithm, by executing the flow-chart as illustrated in Fig. 12. Similar procedure was applied to all the 50 R_a inputs entered in the GUI. Typically, the BpNN

algorithm partitions the data according to the requirements of the system input. It then generates the output for R_a via neural network learning and determines the corresponding R_a values. The values generated are subsequently compared with measured values to calculate deviations.

4. Results and discussion

The GUI stores the experimental data developed as per the L_{27} orthogonal array in a (.mat) format in the MATLAB software. This measured / experimental R_a data is trained, and an error is obtained between the experimental and BpNN predicted R_a . The generated data is trained, tested and validated as per the 70–10–20 % strategy with K fold Cross -Validation technique, shown in Fig. 12. This approach enables rigorous evaluation of the model's performance, as the errors and deviations generated from the output are examined to enhance the

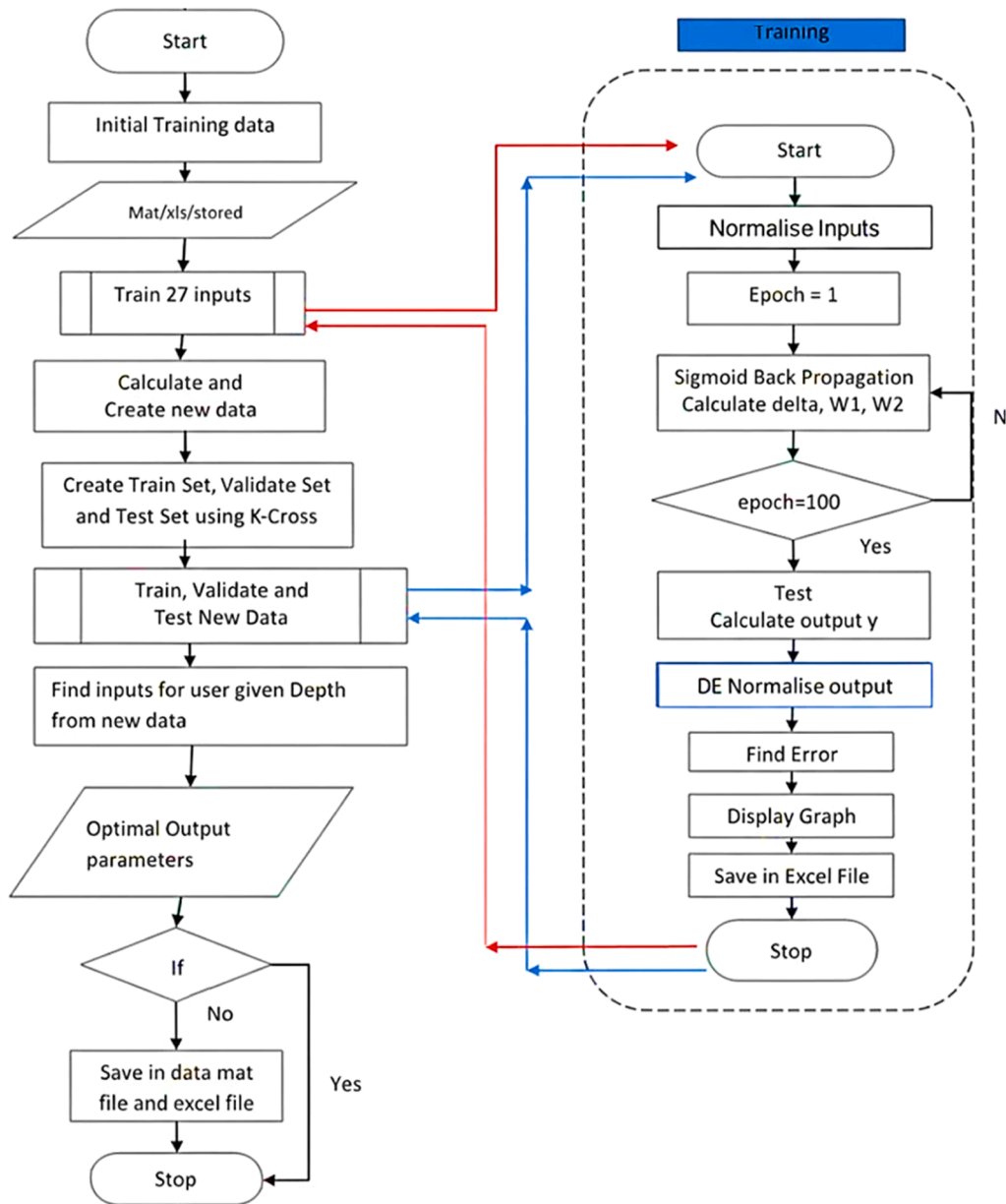


Fig. 12. Process flowchart for the ANN- BPNN algorithm.

understanding of the AWJM process. Furthermore, the preliminary 27 experimental results developed from the Taguchi based DoE are validated to determine the predictive capability of the BpNN algorithm. The reliability of the model is further assessed through the five validation experiments that were conducted conventionally through the AWJM system for comparison with the predictions made by the BpNN algorithm to measure the error.

4.1. Results from the training dataset

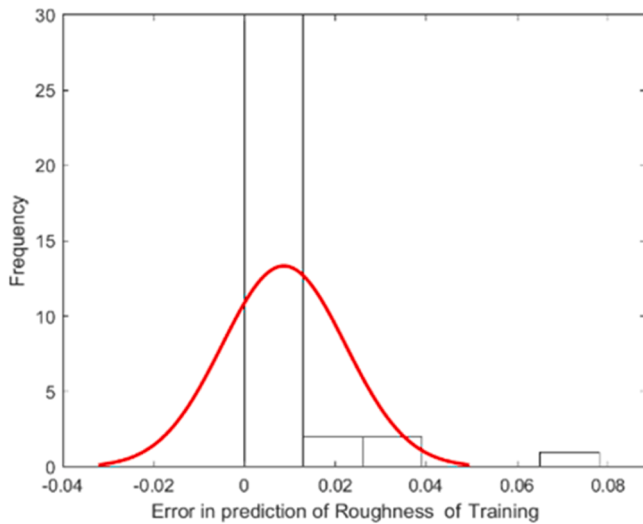
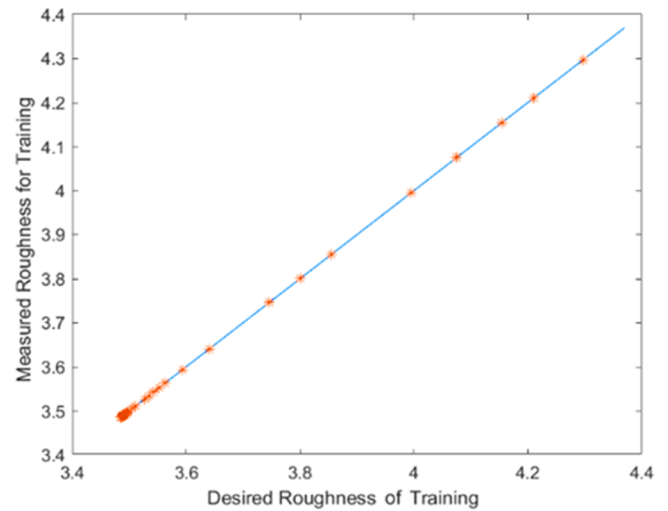
As per the earlier discussion, the K fold Cross-Validation technique was applied. Of the total dataset, 70 % was used for training. In the current scenario, a total of 50 datasets were generated and accordingly, 35 samples (i.e., 70 % of 50) were randomly selected to form the training dataset. From Table 5, it is clear that the highest deviation in R_a , measured at 11.76 % and 10.24 %, corresponds to lower depth of cut (DoC) values. The authors highlight that these deviations occurred specifically at DoC levels of 1 mm and 3 mm, respectively, as reported in Table 4. This makes it very clear that it is very difficult to control the

AWJM parameters for a lower DoC. AWJM at lower DoC values presents a significant challenge due to resilience of the material and flow inconsistencies. This behavior has been extensively reported in previous studies with respect to AWJM studies on various Titanium alloys [7,31]. With increase in the DoC values, deviation becomes less, with the least deviation of 0.04 %. This variation aligns with the studies conducted by Outeiro et al., [32], who reported that the cutting action stabilizes for higher DoC values due to increased material thickness. Therefore, lower DoC's produce higher R_a due to uneven ploughing, and inconsistent abrasive impact distribution, collectively leading to non-uniform erosion patterns. Fig. 13 shows the histogram of errors in prediction of measured R_a with BpNN predictions for the training data set. It clearly shows how the error is distributed across the mean. It displays the error frequencies, and the superimposed red curve indicates normal distribution fit. With majority of the errors focused around 0, it suggests strong predictive accuracy. The superimposed curve shows normal distribution of errors, demonstrating low variance and consistent model behaviour. Similarly, Fig. 14 shows the linear fit between the measured and BpNN predicted R_a for 35 training datasets. This reflects a highly

Table 5

Training dataset (70 %) representing 35 samples with deviations.

Sr. No	W _p (Bar)	T _s (mm/min)	N/O _{dia}	A _{mf} (Kg/min)	A _{os} (mm)	Measured R _a (μm)	BpNN predicted R _a (μm)	Deviation (mm)	Deviation (%)
1	2400	80	2.85	0.16	3.800	4.3698	3.8557	0.5141	11.76
2	2441	83	2.87	0.162	3.816	4.2156	3.784	0.4316	10.24
3	2461	84	2.879	0.163	3.824	4.1154	3.754	0.3614	8.78
4	2482	86	2.889	0.164	3.833	4.0473	3.7203	0.327	8.08
5	2502	87	2.899	0.166	3.841	3.9921	3.6927	0.2994	7.50
6	2543	90	2.919	0.168	3.857	3.8682	3.646	0.2222	5.74
7	2563	91	2.928	0.169	3.865	3.8002	3.6283	0.1719	4.52
8	2584	93	2.938	0.17	3.873	3.7648	3.6101	0.1547	4.11
9	2645	97	2.968	0.173	3.898	3.6405	3.5723	0.0682	1.87
10	2686	100	2.987	0.176	3.914	3.6027	3.5543	0.0484	1.34
11	2727	103	3.007	0.178	3.931	3.5645	3.5413	0.0232	0.65
12	2747	104	3.017	0.179	3.939	3.5468	3.5366	0.0102	0.29
13	2767	106	3.026	0.18	3.947	3.5409	3.532	0.0089	0.25
14	2788	107	3.036	0.181	3.955	3.5271	3.5284	0.0013	0.04
15	2808	109	3.046	0.182	3.963	3.5229	3.5249	0.002	0.06
16	2869	113	3.075	0.186	3.988	3.5070	3.5175	0.0105	0.30
17	2910	116	3.095	0.188	4.004	3.4989	3.514	0.0151	0.43
18	2971	120	3.124	0.191	4.029	3.4889	3.5104	0.0215	0.62
19	2992	121	3.134	0.193	4.037	3.4889	3.5095	0.0206	0.59
20	3012	123	3.144	0.194	4.045	3.4896	3.5087	0.0191	0.55
21	3033	124	3.154	0.195	4.053	3.4859	3.508	0.0221	0.63
22	3073	127	3.173	0.197	4.069	3.4847	3.5069	0.0222	0.64
23	3094	129	3.183	0.198	4.078	3.4856	3.5064	0.0208	0.60
24	3114	130	3.193	0.199	4.086	3.4833	3.506	0.0227	0.65
25	3155	133	3.212	0.202	4.102	3.4870	3.5054	0.0184	0.53
26	3176	134	3.222	0.203	4.110	3.4849	3.5052	0.0203	0.58
27	3196	136	3.232	0.204	4.118	3.4866	3.5049	0.0183	0.52
28	3216	137	3.242	0.205	4.127	3.4851	3.5048	0.0197	0.57
29	3237	139	3.252	0.206	4.135	3.4867	3.5046	0.0179	0.51
30	3257	140	3.261	0.207	4.143	3.4860	3.5046	0.0186	0.53
31	3298	143	3.281	0.209	4.159	3.4866	3.5044	0.0178	0.51
32	3339	146	3.301	0.212	4.176	3.4913	3.5044	0.0131	0.38
33	3359	147	3.31	0.213	4.184	3.4911	3.5044	0.0133	0.38
34	3380	149	3.32	0.214	4.192	3.493	3.5045	0.0115	0.33
35	3400	150	3.33	0.215	4.200	3.4923	3.5045	0.0122	0.35

**Fig. 13.** Histogram of errors in prediction of R_a by BpNN for training dataset.**Fig. 14.** Correlation between BpNN predicted R_a and generated results for training dataset.

accurate training performance of the ANN model with minimum prediction error. When compared to the earlier works [9,32], the BpNN model performed comparatively well. It is also important to note that higher deviations in the R_a were observed for lower DoC values which suggests room for improvement. This could be done by optimizing the AWJM parameters to minimize erosion fluctuations.

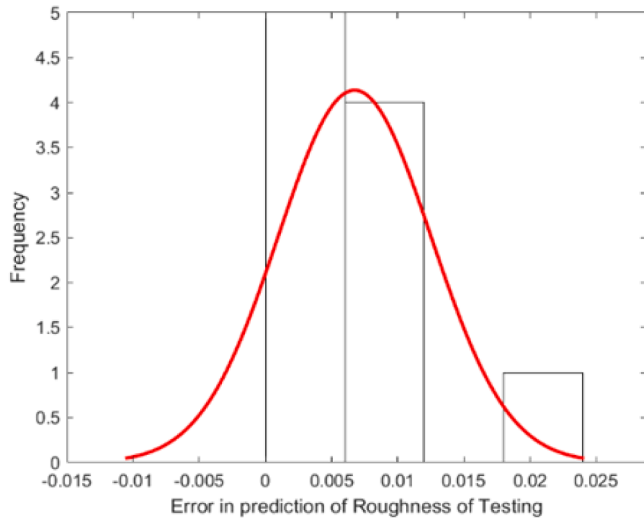
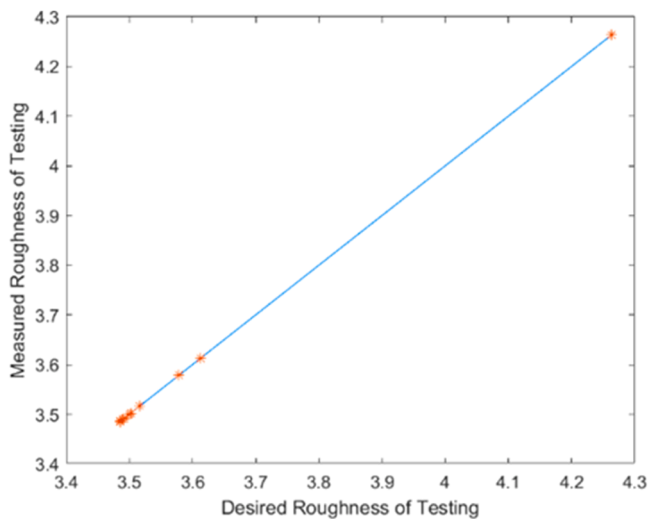
4.2. Results for the testing dataset

In the K fold Cross-Validation technique, the testing phase plays a crucial role, wherein 20 % of the total dataset of 50 samples was allocated for testing. Accordingly, 10 samples (i.e., 20 % of 50) were randomly selected to constitute the testing dataset. The deviation for all the selected data has been presented in Table 6. It can be seen that the highest deviation was 10.45 % and the lowest deviation was 0.33 %. As

Table 6

Testing dataset (20 %) representing 10 samples with deviations.

Sr. No	W_p (Bar)	T_s (mm/min)	N/O dia	A_{mf} (Kg/min)	A_{ps} (mm)	Desired R_a (μm)	Obtained R_a (μm)	Deviation (mm)	Deviation (%)
1	2420	81	2.86	0.161	3.808	4.2674	3.8216	0.4458	10.45
2	2665	99	2.977	0.175	3.906	3.6335	3.5618	0.0717	1.97
3	2706	101	2.997	0.177	3.922	3.578	3.5479	0.0301	0.84
4	2849	111	3.066	0.185	3.98	3.5081	3.5197	0.0116	0.33
5	2931	117	3.105	0.189	4.012	3.4931	3.5127	0.0196	0.56
6	2951	119	3.114	0.19	4.02	3.4935	3.5114	0.0179	0.51
7	3053	126	3.163	0.196	4.061	3.4875	3.5074	0.0199	0.57
8	3135	131	3.203	0.2	4.094	3.4812	3.5057	0.0245	0.70
9	3278	141	3.271	0.208	4.151	3.4848	3.5045	0.0197	0.57
10	3318	144	3.291	0.211	4.167	3.4892	3.5044	0.0152	0.44

**Fig. 15.** Histogram of errors in prediction of R_a by BpNN for testing dataset.**Fig. 16.** Correlation between BpNN predicted R_a and generated results for testing dataset.

per Table 6, the maximum deviation of 10.45 % occurred at lower DoC i. e., 2 mm. This further highlights that lower DoC values correspond to higher deviations for R_a within the testing dataset. When compared to other similar findings reported in [7,32], where the prediction models saw testing errors upto 15 % for R_a , our results are highly favorable. The reduced testing error achieved in this study demonstrates the reliability

of the BpNN algorithm. Fig. 15 shows the histogram of errors in prediction of measured R_a with BpNN predictions for the testing data set. The superimposed red curve is steeper indicating low variance and majority of the errors clustered around 0. This, when compared to the training data set showed slightly smaller deviation suggesting that model does not overfit and maintains better accuracy. Similarly, Fig. 16 shows the linear fit between the measured and BpNN predicted R_a for 10 testing datasets. The data points closely follow the regression line, indicating strong relationship between measured and predicted R_a . The points are clustered around the line suggesting minimal deviation, high accuracy and reliability. Contrasting to the earlier studies that relied heavily on straightforward algorithms, the BpNN leverages its multi-layer architecture and feedback learning mechanism to manage complex relationships more efficiently to enable more accurate predictions [29].

4.3. Results for the validation dataset

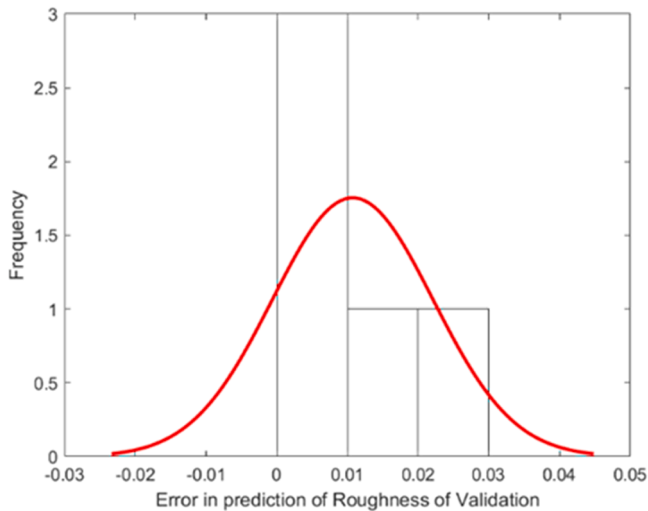
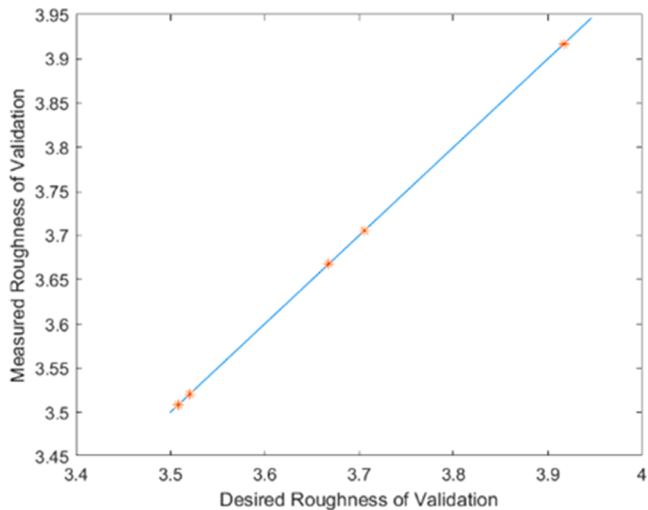
In the K fold Cross-Validation technique, the validation phase plays a crucial role, wherein 10 % of the total dataset of 50 samples was allocated for validation. Accordingly, 5 samples (i.e., 10 % of 50) were randomly selected to constitute the validation dataset. The deviation for all the 5 selected data has been presented in Table 7. It can be seen that the highest deviation was 7.09 % and the lowest deviation was 0.12 %. This dataset was subsequently used to conduct experimental confirmatory tests which aimed at evaluating the efficacy of the K fold Cross-Validation technique for the BpNN algorithm and reliability of the generated output. Fig. 17 shows the histogram of errors in prediction of measured R_a with BpNN predictions for the validation data set. Contrastingly to the training and testing distributions, the validation errors were slightly wider indicating higher variability in the model's performance. The gaussian curve reflected higher variance as it was less peaked, suggesting that the BpNN encounters unrepresented patterns in the validation data. Overall, the validation data set presented a broader error distribution presenting slightly more challenging cases. Similarly, Fig. 18 shows the linear fit between the measured and BpNN predicted R_a for 5 validation data sets. The data points align closely with the reference line, indicating the measured R_a values closely match the target values.

A thorough evaluation of the training, testing, and validation histograms revealed that a low DoC values yielded higher deviations for R_a . It is imperative to note that the abrasive particles used in AWJM vary in hardness, size and shapes. Consequently, the R_a measured for a specific depth of cut (DoC) is highly influenced by these abrasive particles, leading to variability in the final surface finish [33]. These abrasives exhibit unstable abrasive flow rates occasionally, leading to inconsistencies in cutting efficiency [7,12,31]. Additionally, mechanical vibrations also play an important role in jet positioning, introducing significant fluctuations altering the effective jet force [34]. At lower DoC's, even minor changes in the pressure exerted causes disproportionately large effects on material penetration. Moreover, due to the

Table 7

Validation dataset (10 %) representing 5 samples with deviations.

Sr. No	W_p (Bar)	T_s (mm/min)	N/O_{dia}	A_{mf} (Kg/min)	A_{os} (mm)	Desired R_a (μm)	Obtained R_a (μm)	Deviation (mm)	Deviation (%)
1	2522	89	2.909	0.167	3.849	3.9465	3.6666	0.2799	7.09
2	2604	94	2.948	0.171	3.882	3.7049	3.596	0.1089	2.94
3	2624	96	2.958	0.172	3.89	3.6799	3.5825	0.0974	2.65
4	2829	110	3.056	0.184	3.971	3.5180	3.5221	0.0041	0.12
5	2890	114	3.085	0.187	3.996	3.4997	3.5158	0.0161	0.46

**Fig. 17.** Histogram of errors in prediction of R_a by BpNN for validation dataset.**Fig. 18.** Correlation between BpNN predicted R_a and generated results for validation dataset.

high value of Young's Modulus of Ti6Al4V, the deformation is more elastic rather than irregular cutting. Reports also suggest that the Ti-6Al-4V alloy tends to work-harden for smaller DoC's with the initial layers that resist further material removal [7]. From this, the combined influence of abrasive particles, mechanical vibrations, and work-hardening effect of the material ultimately governs the R_a for AWJM of Ti6Al4V.

The architecture considered in the present work involves one input layer with a single hidden layer, and one output layer. Out of those selected, the performance of 1–10–5 architecture produced the best results.

4.4. Model performance

The corresponding network output for training, testing, and validation data sets is presented in the form of regression plots, as shown in Fig. 19. The solid line represents the line of best fit between measured and predicted values for training, testing, validation, and all data sets. The correlation coefficient (R) represents the relation between the R_a values obtained through NN model and the experimental data. A value of $R = 1$ indicates a perfect match between the measured and predicted values [25]. On the other hand, the value of $R = 0$ indicates the relation between measure and predicted values is non-linear. The testing data showed the best performance for the selected neural network architecture. The neural network architecture examined in this study consisted of one input layer and one hidden layer, and one output layer. Among the configurations, the architecture of (1–10–5) was found to be optimal and yielded a correlation coefficient of $R = 0.9728$ with a mean squared error of approximately 10^{-5} between epochs 2000–3000 (Fig. 20). The convergence behaviour of the model suggests a stable learning process with no significant signs of overfitting across the training, testing, and validation datasets.

4.5. Comparison of BpNN predicted R_a with experimental R_a

Table 8 shows the comparison of BpNN generated R_a with the experimental R_a of the Taguchi-DoE based 27 experimental values. The highest deviation was observed for Experiment no. 2, with an error of 0.0949 (2.41 %), representing the least accurate prediction. Subsequently, the lowest deviation was for Experiment 9, with only 0.0005 mm (0.01 %), showing almost perfect prediction. The overall deviation for all the 27 trials was low, confirming its robust learning capacity. This close agreement between the experimental and BpNN predicted R_a values indicated that the network was successfully able to capture non-linear interactions amongst process parameters. This further validated the suitability of the BpNN algorithm in modelling R_a in the AWJM process. Fig. 21 shows the error variation in terms of epoch for the Taguchi based R_a data set. An epoch represents one complete iteration through which the model processes the entire training dataset once during the learning phase [35]. It can be seen that the error sharply decreases during the early phase of training. As the training progresses, the error fluctuates slightly and gradually stabilizes, demonstrating the BpNN's ability to modify its weights to minimize residual errors. The final convergence nears zero demonstrating effective training and generalization capability of the network.

4.6. Experimental validation and observations

Table 9 summarizes five validation trials comparing experimentally measured surface roughness (R_a) with those predicted by the BpNN model. Confirmatory experiments were conducted, and their corresponding R_a values were recorded. Each trial lists the associated parameters W_p , T_s , A_{mf} , A_{os} , N/O_{dia} , alongside the experimentally obtained R_a values. The BpNN predictions exhibit strong agreement with the desired R_a values, with deviation values generally remaining in the range of 0.12–7.09 %. The table also reports the measured validation-experiment R_a values, which remain reasonably consistent with the

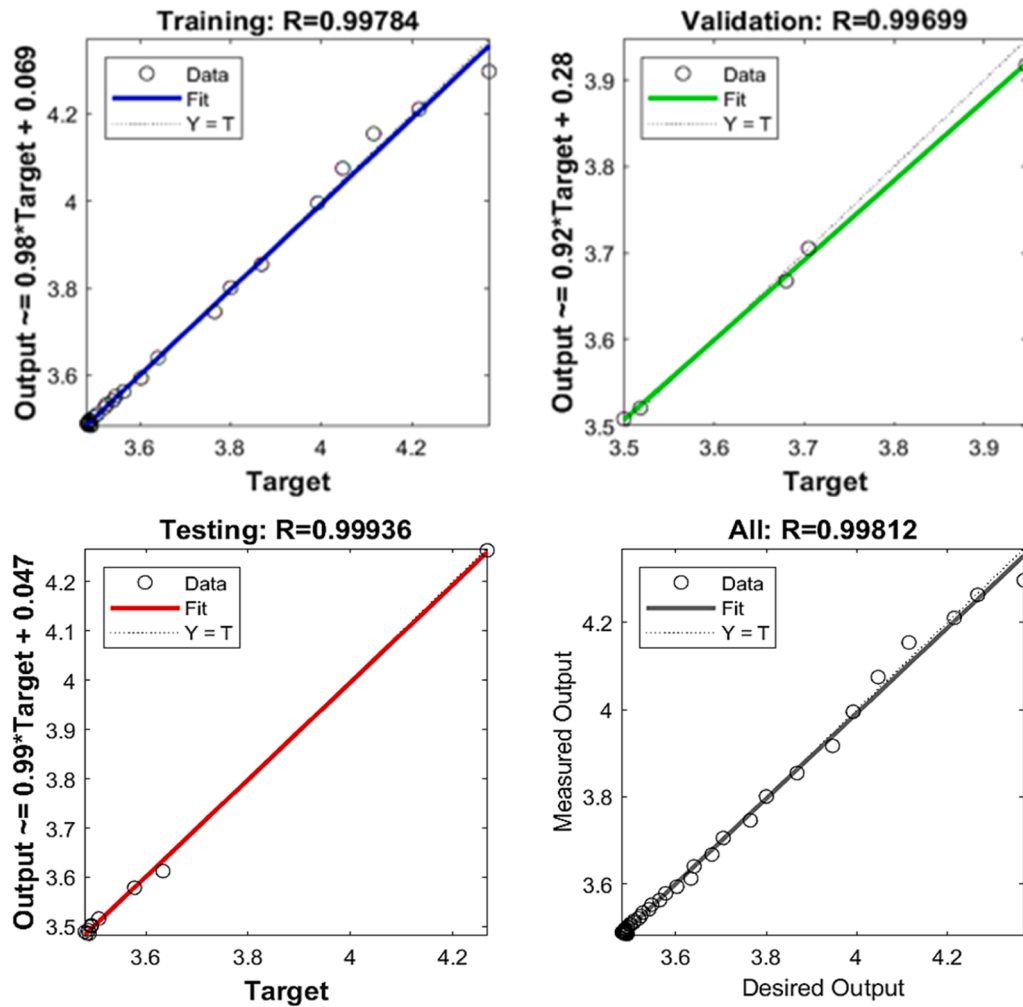


Fig. 19. Regression plot for architecture 1–10–5.

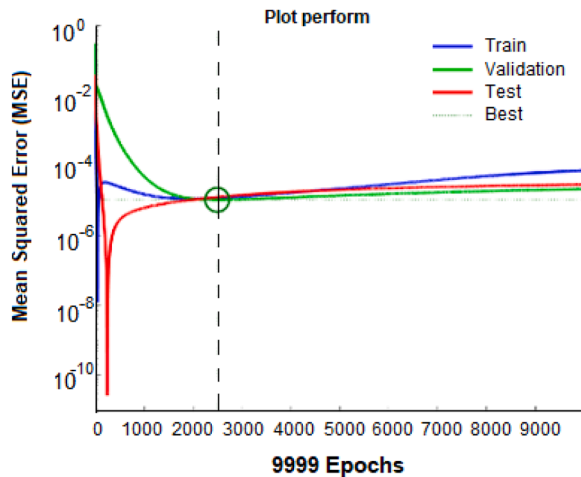


Fig. 20. Validation performance for the ANN pattern.

target R_a values. Overall, the deviations in the final column indicate that the validated R_a values differ from the desired R_a by approximately 5–11 %, indicating acceptable predictive accuracy. The fundamental reason for this difference in R_a values was primarily due to the machine vibrations during experimentation which cannot be fully avoided [7]. Machine vibrations in AWJM tend to cause fluctuations in jet alignment

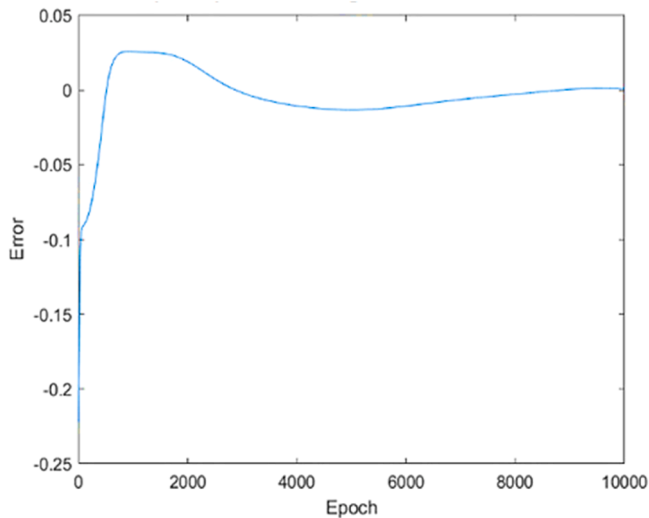
that highly influence jet velocity resulting in inconsistent particle strike patterns on the surface of the specimen. As a result, the R_a deteriorates due to inconsistent erosion and micro-cutting behaviour [32]. Fig. 22 depicts the comparison between desired R_a , BpNN predicted R_a , and R_a obtained through validation experiments. These findings indicate that the model can generalise well beyond the training dataset, making it a reliable tool for pre-process optimisation of AWJM parameters. Such predictive capability reduces the need for extensive experimental trials, saving both time and resources in industrial applications.

4.7. SEM morphology

Visual inspection from Fig. 23 shows the surface profiles of the five validation specimens, and their corresponding SEM images are shown in Fig. 24. The R_a variations observed across all the validation specimens are governed by the combined influence of all the five process parameters which alter the nature of particle energy, distribution, and erosion mechanisms during AWJM. Among the five specimens, the second and third samples with R_a values of 3.94 μm and 3.97 μm (Fig. 23), exhibited the smoothest surface. This is reflected in the SEM image (Fig. 24a), which shows shallower grooves, uniform erosion lines, minimal cracking and fewer crater marks, indication consistent material removal process. This behaviour indicates that the specimen was subjected to relatively lower erosive energy, either due to reduced abrasive mass flow rate, lower water pressure, or a lower traverse speed. Under such conditions, the abrasive particles strike the surface with less kinetic energy, producing smoother grooves and reducing the likelihood of

Table 8Deviation for R_a by BpNN predicted with experimental values of Taguchi-DoE generated values.

Exp. No.	W_p (Bar)	T_s (mm/min)	N/O_{dia}	A_{mf} (Kg/min)	A_{os} (mm)	Experimental R_a (μm)	BpNN predicted R_a (μm)	Deviation (mm)	Deviation (%)
1	2400	80	2.85	0.16	3.8	4.330	4.3587	0.0287	0.66
2	2400	80	2.85	0.16	4.0	3.940	3.8451	0.0949	2.41
3	2400	80	2.85	0.16	4.2	3.837	3.8834	0.0464	1.21
4	2400	100	3.04	0.18	3.8	5.720	5.6056	0.1144	2.00
5	2400	100	3.04	0.18	4.0	3.900	3.9191	0.0191	0.49
6	2400	100	3.04	0.18	4.2	4.727	4.7198	0.0072	0.15
7	2400	150	3.33	0.215	3.8	4.784	4.7837	0.0003	0.01
8	2400	150	3.33	0.215	4.0	4.891	4.8935	0.0025	0.05
9	2400	150	3.33	0.215	4.2	4.998	4.9967	0.0013	0.03
10	2900	80	3.04	0.215	3.8	4.723	4.7254	0.0024	0.05
11	2900	80	3.04	0.215	4.0	3.547	3.5456	0.0014	0.04
12	2900	80	3.04	0.215	4.2	3.643	3.6470	0.0040	0.11
13	2900	100	3.33	0.16	3.8	4.300	4.3030	0.0030	0.07
14	2900	100	3.33	0.16	4.0	4.620	4.6225	0.0025	0.05
15	2900	100	3.33	0.16	4.2	4.200	4.1987	0.0013	0.03
16	2900	150	2.85	0.18	3.8	4.183	4.1863	0.0033	0.08
17	2900	150	2.85	0.18	4.0	4.269	4.2711	0.0021	0.05
18	2900	150	2.85	0.18	4.2	4.292	4.2949	0.0029	0.07
19	3400	80	3.33	0.18	3.8	3.427	3.4301	0.0031	0.09
20	3400	80	3.33	0.18	4.0	3.730	3.7285	0.0015	0.04
21	3400	80	3.33	0.18	4.2	3.420	3.4554	0.0354	1.04
22	3400	100	2.85	0.215	3.8	4.307	4.3050	0.0020	0.05
23	3400	100	2.85	0.215	4.0	3.863	3.8647	0.0017	0.04
24	3400	100	2.85	0.215	4.2	3.867	3.8655	0.0015	0.04
25	3400	150	3.04	0.16	3.8	4.637	4.6345	0.0025	0.05
26	3400	150	3.04	0.16	4.0	3.527	3.5229	0.0041	0.12
27	3400	150	3.04	0.16	4.2	3.567	3.5651	0.0019	0.05

**Fig. 21.** Variation of error in prediction of R_a with the number of epochs.

micro-cracking or crater formation [36,37]. For the fifth specimen, i.e., ($R_a \approx 4.14 \mu m$) of Fig. 23, the surface showed slightly pronounced erosion features. In the SEM image (Fig. 24b), micro-ploughing and micro-cutting patterns are visible, suggesting that the cutting occurred

under the influence of particle momentum [31]. This primary reason for this was due to an increased N/O_{dia} that widens the jet, reducing kinetic energy delivered to the surface and creating dispersed erosion [38]. This causes waviness, discontinuous lay patterns in the form of micro-cutting or fracture, and micro-ploughing features [33,38]. It is also reported by Chaturvedi et al., [39] that while the W_p and T_s were adequate, and A_{os} or A_{mf} was slightly above the optimal window, there is a moderate increase in surface irregularity. The first and fourth specimen with an R_a of approximately $4.39 \mu m$ and $4.74 \mu m$, displayed relatively higher erosion characteristics, exhibiting the highest roughness values, shown in the form of deeper grooves, ridge formation, and significant brittle micro-chipping (Fig. 24c). These features are indicative of the excessive pressure and abrasive mass flow rate, where particle-particle collisions prior to impact, reduce cutting efficiency and generate crater-like damage and micro-chipping [38]. The formation of ridges and discontinuous surface waves also suggests an increased stand-off effect caused by an unfavourable N/O_{dia} , resulting in loss of jet coherence and a wider, less focused cutting [37,39]. A higher T_p also influences R_a as higher speeds reduce jet-material interaction time, leaving behind uncut ridges and deeper grooves.

These experimental observations correlate well with the mechanistic descriptions seen in the SEM images. Lower-roughness specimens display uniform erosion lines with minimal cracking, corresponding to lower water pressure and traverse speed, adequate abrasive mass flow, appropriate orifice size, and favourable nozzle-to-orifice diameter ratio. Higher-roughness specimens show aggressive erosion, deeper streaks,

Table 9Data validation with BpNN algorithm and validation experiments for R_a .

SI. No	W_p	T_s	N/O_{dia}	A_{mf}	A_{os}	Desired R_a (μm)	BpNN predicted R_a (μm)	Deviation (Desired R_a with BpNN) %	Validation experiments for R_a , (mm)	Deviation (Desired R_a with Validated R_a) (%)
1	2500	80	3.42	540	5.2	3.9465	3.6666	7.09	4.39	10.15
2	2600	90	3.42	450	4.8	3.7049	3.596	2.94	3.94	5.980
3	2700	100	3.42	400	4.6	3.6799	3.5825	2.65	3.97	7.550
4	2800	110	3.04	340	4.4	3.5180	3.5221	0.12	4.75	13.13
5	2900	120	3.04	280	3.8	3.4997	3.5158	0.46	4.14	10.70

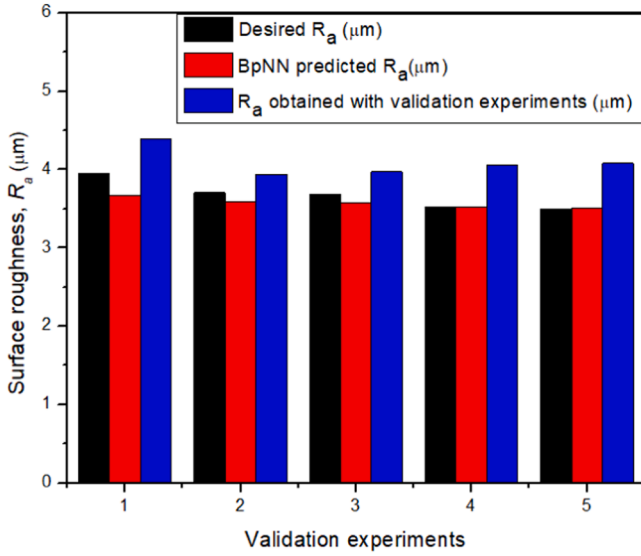


Fig. 22. Comparison of experimental R_a with BpNN predictions and validation experiments.

and partially fractured zones, consistent with high abrasive mass flow and sub-optimal nozzle-to-orifice diameter ratio. The overall identification from SEM morphology confirms that abrasive mass flow rate and nozzle-to-orifice diameter ratio are critical for roughness, while water pressure, traverse speed, and orifice size exert control over particle motion and erosion behaviour. Conversely, optimal ranges of these five parameters yield smoother surfaces with finer abrasion marks, minimal crater formation, and improved directional consistency - attributes required for aerospace-grade surface integrity.

4.8. Sensitivity analysis

To further analyse the influence of process parameters, a sensitivity analysis was conducted to quantify influence of input process parameters on AWJM of Ti6Al4V. Sensitivity analysis is conducted on the basis of the trained BpNN model, using the network weights and biases learned from the experimental (L_{27}) data. This sensitivity analysis employs a Garson [40] based expression, as referenced by Hernandez *et al.* [41], Hamzaoui *et al.* [42], and Reyes-Tellez *et al.* [43], with subsequent enhancements by Goh [44]. The method evaluates parameter significance by analysing the weighted connections between the input and

hidden layer, as well as between the hidden and the output layer. The equation of relative importance is as per Eq. 2 [44].

$$I_j(\%) = \frac{\sum_{m=1}^{N_h} \left(\frac{|W_{jm}^{i,h}|}{\sum_{n=1}^{N_i} |W_{nm}^{i,h}|} \right) \times W_{ml}^{h,o}}{\sum_{n=1}^{N_i} \left[\sum_{m=1}^{N_h} \frac{|W_{nm}^{i,h}|}{\sum_{n=1}^{N_i} |W_{nm}^{i,h}|} \times W_{ml}^{h,o} \right]} \quad (2)$$

where, I_j is the importance of j^{th} parameter on the output, N_i and N_h represent the number of neurons in the input and hidden layer, respectively, W are the weighted connections. The subscripts i, h , and o , represent the input, hidden and output layers, respectively. Similarly, n, m , and l , represent the number of neurons in the input, hidden, and output layers, respectively.

The weights and biases of the current neural network analysis for AWJM of Ti6AL4V are provided in Table 10. The use of Eq. 2 showed that the input process parameters have a significant influence, as seen in Fig. 25, showing the relative importance of all five input variables W_p , T_s , A_{mf} , A_{os} , N/O_{dia} on R_a of AWJM of Ti6AL4V. It is clearly seen that all variables have some influence on R_a . The parameter water pressure (W_p) showed highest influence on R_a with 36.7 %, followed by traverse speed (T_s) with 29.7 %. The next notable influence was of N/O_{dia} with 13.4 %. The rest of the parameters i.e., A_{os} and A_{mf} influenced by 10.2 % and 10 %, respectively. It is very clear from the sensitivity analysis that W_p and T_s are the critical parameters influencing R_a . Their high contribution weights indicate strong control over particle concentration and jet penetration characteristics. As a result, variations in these parameters have a pronounced impact on erosion mechanisms and the final R_a values.

4.9. Contour plots

Contour plots are used to provide a visual representation of influence of two input variable on the output response by representing constant-value regions through contour lines. These plots identify sensitivity trends, optimal parameters, and non-linear interactions that may not be apparent from tabular data. The current study has used contour plots for observing R_a variations under variable parameter conditions. They also support decision-making by clearly highlighting regions of improvement or instability. Fig. 26 represents the contour plots for R_a for all 10 possible two parameter combinations involving W_p , T_s , A_{mf} , A_{os} , N/O_{dia} .

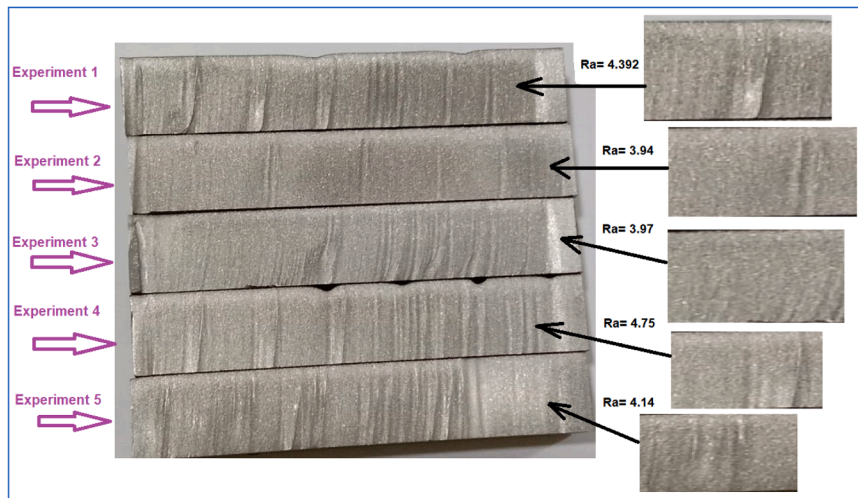


Fig. 23. Measured R_a for validation experiments performed as per Table 9.

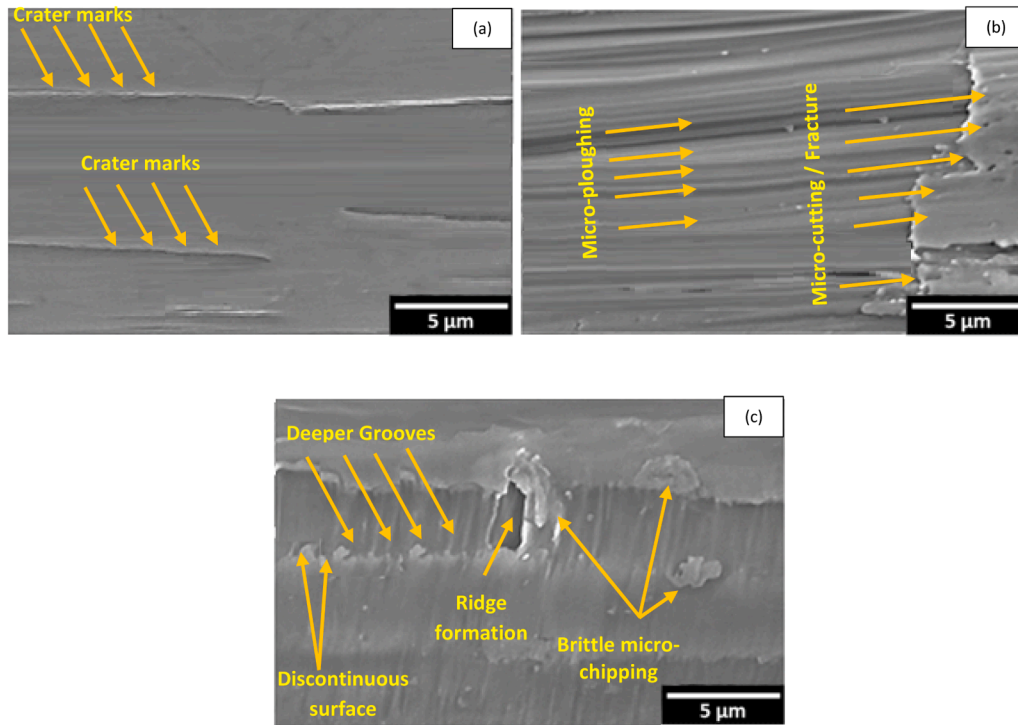
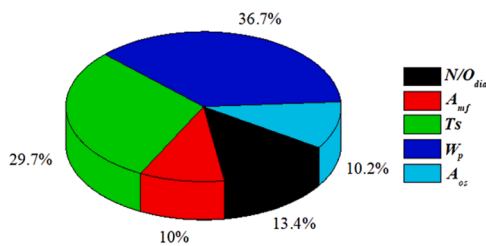
Fig. 24. SEM images for different R_a . [38]

Table 10

Weights and biases for the neural network model.

W_{ij}	Hidden neurons: j (1,..., 10)									
Input i (1,...,6)	-0.7044	0.8062	-0.1322	-1.2366	-4.1209	0.1156	3.1101	-1.9202	0.5533	12.012
	22.884	-16.446	-0.9012	3.6612	18.012	-17.912	-11.602	5.1601	19.461	9.1211
	-12.112	16.928	0.7452	1.8810	2.0454	1.0612	4.5690	1.2233	10.881	-1.6630
	0.6913	-2.9910	0.0163	-3.0123	9.0312	3.9910	21.662	-6.0145	30.012	5.4421
	-1.2451	20.469	-2.4102	0.8812	-6.6712	14.312	-0.6123	0.1212	-0.9901	-0.6633
	18.902	-17.513	1.6610	0.7712	0.4432	-3.4411	4.9912	7.6634	-11.402	3.2201
W_{ij} ($k = 1$)	0.4912	1.3452	29.402	-0.6840	3.0123	6.5534	-16.434	-0.7440	-0.4071	0.4440
$b1_{(k)}$	-30.405	-11.410	4.1032	0.1233	-4.0101	-0.9621	0.4512	0.1600	0.1233	6.4213
$b2_{(s)}$	-27.545									

Fig. 25. Sensitivity analysis for R_a .

These contour plots were generated using the Taguchi based L_{27} Orthogonal array, where pairs of input variables were analysed simultaneously to evaluate their interactive influence on R_a .

Based on the 10 counter plots shown on Fig. 26, the most influential parameter affecting surface roughness is the water pressure followed by traverse speed. Water pressure shows the strongest and most consistent effect across nearly all parameter interactions whereas higher pressures about 3000 bar clearly respond to lower surface roughness values in the range 3.7–4 μm . This trend appears in multiple plots indicating that pressure directly governs the jet energy particle acceleration and erosion mechanics responsible for smoother material removal. In contrast lower

pressures less than 2600 bar consistently produce rougher surfaces as seen from the yellow-green regions indicating R_a values above 4.5 μm . The second most influential parameter was traverse speed which shows a clear relationship where lower speeds 80–100 mm/min yield smoother surfaces due to longer jet material interaction while higher speeds reduce exposure time and result in rougher surfaces. This behaviour is evident in $W_p - T_s$, $T_s - N/O_{dia}$ and $T_s - A_{mf}$ plots where T_s significantly alters the counter gradients. Although parameters such as A_{mf} , N/O_{dia} and A_{os} contribute to variations their effects are completely localized and weaker. Overall, the counter maps confirm that increasing water pressure and optimizing traverse speed are the dominant factors for minimizing R_a in AWJM of Ti6Al4V.

The observed surface features closely follow the quantitative surface roughness (R_a) trends obtained from sensitivity analysis and counter plots. A more detailed qualitative - quantitative correlation of the independent influence of each parameter in the formation of the SEM features has been provided in Table 11.

5. Conclusions

The current work developed and validated a machine learning-based backpropagation neural network (BpNN) model to predict surface roughness in abrasive water jet milling (AWJM) of Ti6Al4V.

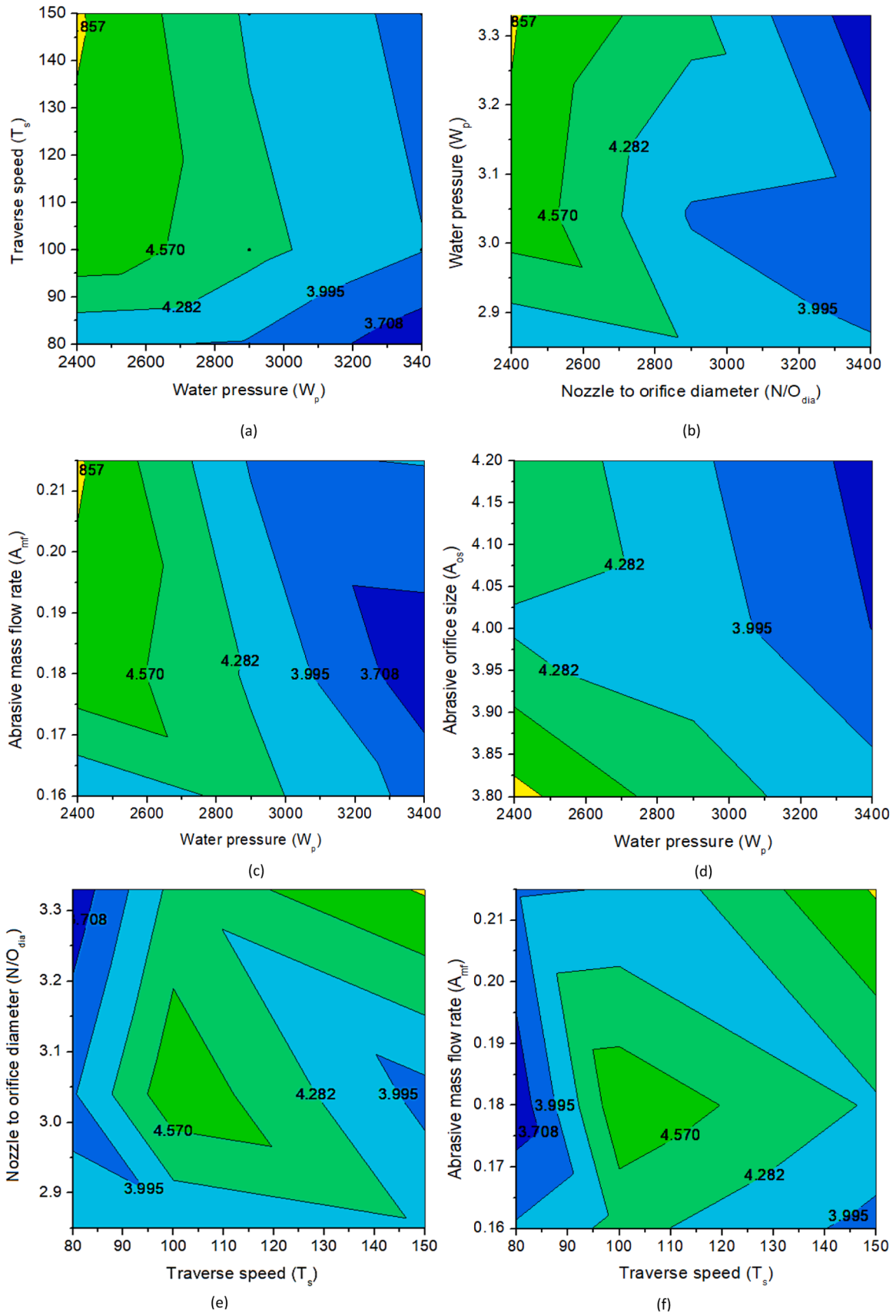


Fig. 26. Contour plots for R_a based on input variables, (a) $W_p - T_s$, (b) $W_p - N/O_{dia}$, (c) $W_p - A_{mf}$, (d) $W_p - A_{os}$, (e) $T_s - N/O_{dia}$, (f) $T_s - A_{mf}$, (g) $T_s - A_{os}$, (h) $N/O_{dia} - A_{mf}$, (i) $N/O_{dia} - A_{os}$, (j) $A_{mf} - A_{os}$.

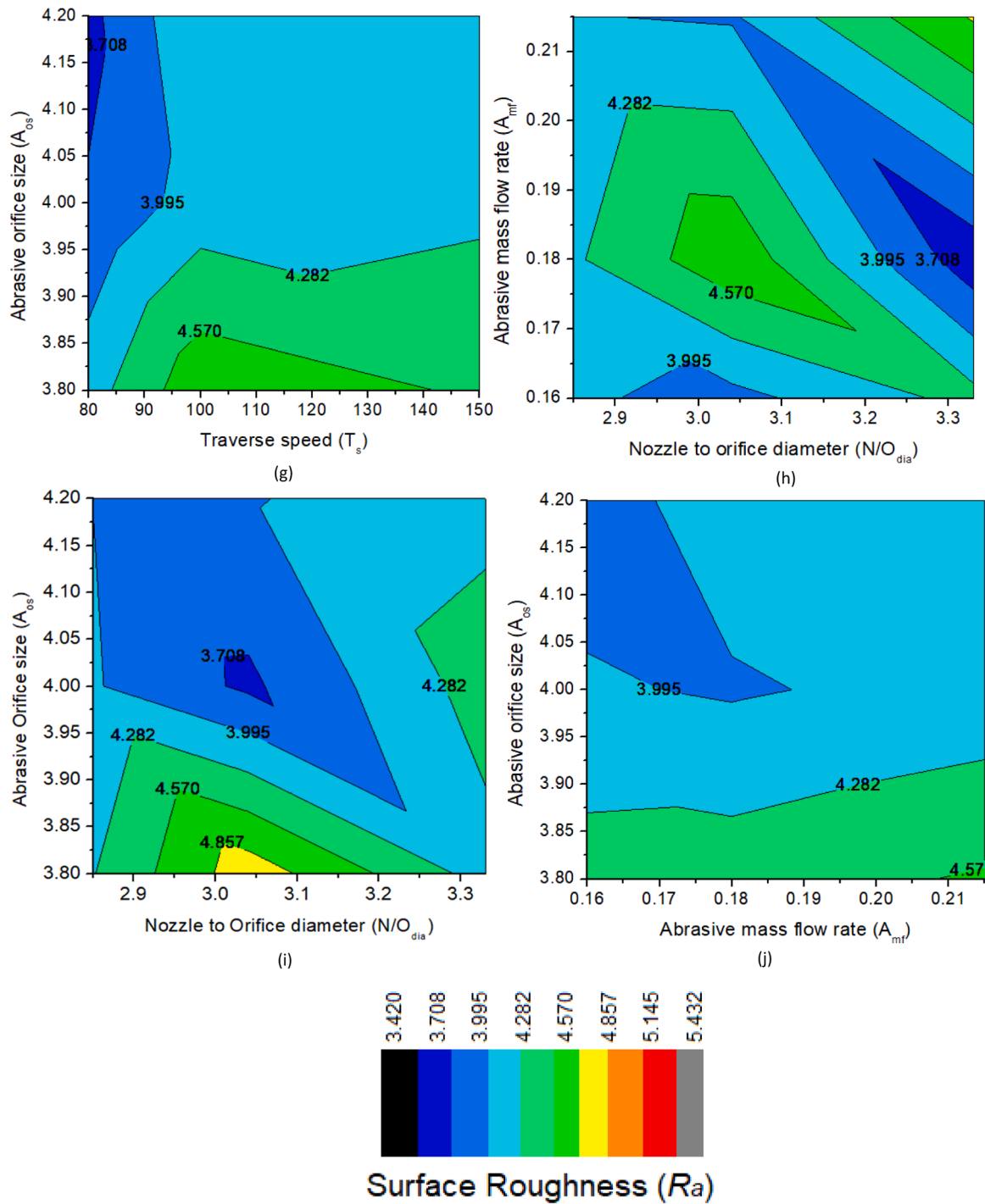


Fig. 26. (continued).

Experiments were conducted using a Taguchi based L_{27} orthogonal design, and the resulting data were divided into training (70 %), testing (20 %), and validation (10 %) data sets. The algorithm demonstrated several capabilities that have not been reported previously in the literature for surface roughness of Ti6Al4V using AWJM. This section summarizes the key findings, contributions, and limitation, as outlines below:

- The BpNN algorithm was able to predict five important dynamic optimal parameters as output for R_a which plays a crucial role in the AWJM of Ti6Al4V.
- The BpNN algorithm was able to accurately predict the R_a for the Taguchi-DoE experiments, maintaining a maximum deviation of 2.5 %.
- The BpNN algorithm generated 50 new experimental cases which were automated for allocation for K fold Cross-Validation, with 70 % used for training, 20 % used for testing, and 10 % used for validation. Amongst all, the testing data set exhibited the strongest performance for the selected 1–10–5 architecture, achieving an exceptionally high R -value of 0.99936.
- Confirmatory experiments were carried out for R_a and compared against the 10 % validation data set. The results showed that the

Table 11

Parameter- based correlation of SEM morphology with sensitivity analysis and contour plots.

Sl. No.	Parameter change	Physical mechanism	Anticipated SEM feature	Quantitative support
1.	High W_p	higher particle momentum and impact energy	Uniform micro-cutting, uniform erosion	Sensitivity analysis: W_p (36.7 %); contour plots show lower R_a bands (~ 3.71 – $4.0 \mu\text{m}$) at high W_p (~ 3000 – 3400 bar) for W_p - T_s and W_p - A_{mf} pairings.
2.	Low W_p ($\leq 2600 \text{ bar}$)	lower erosive energy	Incomplete erosion, striations, waviness	Contour plots show higher R_a bands (4.57 – $4.86 \mu\text{m}$) for low W_p (~ 2400 – 2600 bar) in W_p - T_s and W_p - N/O_{dia} contours.
3.	High T_s (110–150 mm/min)	low interaction time, increase in jet lag	Formation of ridges, discontinuous striations, deeper grooves	Sensitivity analysis: T_s (29.7 %); contour plots show R_a migrating from (~ 3.7 – $3.99 \mu\text{m}$) to (~ 4.28 – $4.57 \mu\text{m}$) for increasing T_s for W_p - T_s and T_s - N/O_{dia} contours.
4.	Low T_s (80–100 mm/min)	longer interaction time, uniform erosion	Uniform erosion lines, shallow grooves	Contour plots show consistent low R_a bands from (~ 3.7 – $3.99 \mu\text{m}$) for T_s (80–100 mm/min), confirming smoother morphology.
5.	High A_{mf} (0.16 – 0.215 kg/min)	increase in particle-particle collisions	Shallow and irregular grooves	Contour plots show R_a increasing from ranges (~ 3.7 – $3.99 \mu\text{m}$) to (~ 4.28 – $4.57 \mu\text{m}$) in the W_p - A_{mf} and A_{mf} - T_s contours.
6.	High N/O_{dia} (≈ 3.2 – 3.33)	jet spreading	Crater marks, micro-ploughing	Contour plots show R_a increasing from ranges (~ 3.7 – $3.99 \mu\text{m}$) to (~ 4.28 – $4.57 \mu\text{m}$) for increasing N/O_{dia} in the W_p - N/O_{dia} and T_s - N/O_{dia} contours.
7.	High A_{os} (≈ 4.0 – 4.2 mm)	reduced jet coherence	Inconsistent erosion	Contour plots show R_a transitions from ranges (~ 3.7 – $4.57 \mu\text{m}$) for increasing A_{os} beyond 4.0 mm in the W_p - A_{os} and T_s - A_{os} contours.

BpNN algorithm was able to accurately predict R_a with deviation values in the range of 0.12–7.09 %.

- The SEM observations confirm that R_a in AWJM of Ti6Al4V is predominantly governed by particle energy, jet coherence, and erosion dynamics influenced by pressure, traverse speed, abrasive mass flow rate, and abrasive orifice size. The images clearly demonstrate that improper parameter combinations amplify jet divergence and particle impacts, leading to surface irregularities.
- The sensitivity analysis and the contour plots confirmed that all the five input parameters influence R_a with water pressure and traverse speed emerging as the most dominant contributors. Their strong weighting highlights their critical role in governing particle concentration and jet penetration.

- The current study demonstrates that adaptive neural network approach provides strong predictability, outperforming conventional regression and machine learning techniques.
- The present study presents a strong predictive capability of R_a in AWJM of Ti6Al4V; however, certain limitations need to be considered. The developed BpNN model is material specific, as it has been tested for the experimental dataset from Ti6Al4V. Additionally, abrasive characteristics such as, abrasive particle sizes and shapes, and particle fragmentation have not been explicitly considered, despite their known influence on R_a . Furthermore, the current model is highly dependent on selected machining parameters and their levels; therefore, its application to different machining conditions would require retraining and recalibration.
- Researchers could try to explore the possibility of inculcating numerical simulations through software's such as computational fluid dynamics and OpenFOAM along with the available experimental data, to generate hybrid datasets. This approach will further enhance the predictive capabilities of machine learning algorithms for AWJM processes.

CRediT authorship contribution statement

Mohammad Abdul Malik: Funding acquisition, Formal analysis, Data curation. **Muneer Baig:** Resources, Formal analysis, Data curation. **Abdul Aabid:** Writing – review & editing, Methodology, Conceptualization. **Asma Begum:** Methodology, Investigation, Conceptualization. **Suhas P.:** Writing – original draft, Methodology, Conceptualization. **Jaimon Dennis Quadros:** Writing – original draft, Methodology, Investigation. **Yakub Iqbal Mogul:** Writing – original draft, Methodology, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

References

- [1] H. Wang, Y. Li, Q. Chen, B. Xu, J. Zhang, Research progress in abrasive water jet processing: principles, mechanisms and applications, *Materials* 16 (18) (2023) 6472.
- [2] H.Y. Ting, M. Asmelash, A. Azhari, T. Alemu, K. Saptaji, Prediction of surface roughness of titanium alloy in abrasive waterjet machining process, *Int. J. Interact. Des. Manuf.* 16 (1) (2022) 281–289.
- [3] K. Fuse, A. Patil, B. Sahoo, Abrasive waterjet machining of titanium alloy using an integrated approach of Taguchi-based Passing Vehicle Search algorithm, *Int. J. Interact. Des. Manuf.* 19 (2025) 2249–2263.
- [4] Y.I. Mogul, J.D. Quadros, S.A. Khan, M. Agrawal, I. Kumar, S. Shaik, C.A. Saleel, A. Saxena, Statistical modelling of depth milling in Ti6Al4V using abrasive water jet machining, *Proc. Inst. Mech. Eng. Part E J. Process Mech. Eng.* (2024), 09544089231223789.
- [5] A.K. Dubey, Y. Kumar, S. Kumar, Optimizing parameters of AWJM for Ti6Al4 V grade 5 alloy using grey entropy weight method: a multivariable approach, *J. Inst. Eng. (India) Ser. C* 106 (1) (2025) 181–195.
- [6] S. Zhang, H. Zhang, C. Wang, G. Zhou, J. Cheng, Z. Zhang, X. Wang, L. Chen, Prediction of flow and dynamic recrystallization behavior based on three machine learning methods for a novel duplex-phase titanium alloy, *Intermetallics* 175 (2024) 108523.

- [7] Y.I. Mogul, I. Mogul, J.D. Quadros, M. Mohin, A. Aabid, M. Baig, M.A. Malik, Prediction of cutting depth in abrasive water jet machining of Ti-6Al-4V alloy using back propagation neural networks, *Results Eng.* 25 (2025) 104520.
- [8] Z. Liu, H. Zhang, S. Zhang, J. Cheng, Y. He, G. Zhou, J. Liu, S. Song, L. Chen, A machine learning method approach for designing novel high strength and plasticity metastable β titanium alloys, *Progress Nat. Sci. Mater. Int.* 35 (1) (2025) 156–165.
- [9] D. Doreswamy, S.K. Bhat, P. Hiremath, D.S. Shreyas, A. Bongale, ANN-based predictive modelling of the effect of abrasive water-jet parameters on the surface roughness of AZ31 Mg alloy, *Manuf. Rev.* 11 (2024) 21.
- [10] R. Prabhu, M. Kanthababu, Prediction of surface roughness and depth of cut in abrasive waterjet milling of alumina ceramic using machine learning algorithms, *Expert Syst. Appl.* 246 (2024) 123168.
- [11] F. Kartal, H. Gökkaya, Effect of abrasive water jet turning process parameters on surface roughness and material removal rate of AISI 1050 steel, *Mater. Test.* 57 (9) (2015) 773–782.
- [12] U. Çaydaş, A. Haşçalık, A study on surface roughness in abrasive waterjet machining process using artificial neural networks and regression analysis method, *J. Mater. Process. Technol.* 202 (1–3) (2008) 574–582.
- [13] J.B. Chandar, N. Lenin, C. Rathinasuriyan, Exploring surface integrity: experimental investigation into abrasive waterjet deep hole drilling on ss 316L for biomedical applications, *J. Alloy. Metall. Syst.* 8 (2024) 100109.
- [14] O. Cavusoglu, A multi-response investigation of abrasive waterjet machining parameters on the surface integrity of twinning-induced plasticity (TWIP) steel, *Materials* 18 (14) (2025) 3404.
- [15] A. Perec, E. Kawecka, F. Pude, Enhancing high-alloy steel cutting with abrasive water injection jet (AWIJ) technology: an approach using the response surface methodology (RSM), *Materials* 17 (16) (2024) 4020.
- [16] M. Płodzień, Ł. Żyłka, K. Żak, S. Wojciechowski, Modelling the kerf angle, roughness and waviness of the surface of inconel 718 in an abrasive water jet cutting process, *Materials* 16 (15) (2023) 5288.
- [17] P. Ramesh, K. Mani, Prediction of surface roughness using machine learning approach for abrasive waterjet milling of alumina ceramic, *Int. J. Adv. Manuf. Technol.* 119 (1) (2022) 503–516.
- [18] A.A. Tsegaw, F.J. Shiou, S.P. Lin, Ultra-precision polishing of N-Bk7 using an innovative self-propelled abrasive fluid multi-jet polishing tool, *Mach. Sci. Technol.* 19 (2) (2015) 262–285.
- [19] P. Suhas, J.D. Quadros, Y.I. Mogul, M. Mohin, A. Aabid, M. Baig, O.S. Ahmed, A review of mechanical metamaterials and additive manufacturing techniques for biomedical applications, *Mater. Adv.* 6 (2025) 887–908.
- [20] A. Rowe, A. Pramanik, A.K. Basak, C. Prakash, S. Subramaniam, A.R. Dixit, N. Radhika, Effects of abrasive waterjet machining on the quality of the surface generated on a carbon fibre reinforced polymer composite, *Machines* 11 (7) (2023) 749.
- [21] S. De la Rosa, L. Rodríguez-Parada, M.B. Ponce, P.F. Mayuet Ares, The abrasive water jet cutting process of carbon-fiber-reinforced polylactic acid samples obtained by additive manufacturing: a comparative analysis, *J. Compos. Sci.* 8 (10) (2024) 437.
- [22] C. Felhő, K. Kun-Bodnár, Z. Maros, Comparison of 2D and 3D surface roughness parameters of AlMgSi0.5 aluminium alloy surfaces machined by abrasive waterjet, *J. Manuf. Mater. Process.* 9 (3) (2025) 80.
- [23] M. Ficko, D. Begic-Hajdarevic, M. Cohodar Husic, L. Berus, A. Cekic, S. Klancnik, Prediction of surface roughness of an abrasive water jet cut using an artificial neural network, *Materials* 14 (11) (2021) 3108.
- [24] J. Holmberg, A. Wretland, J. Berglund, Abrasive water jet milling as an efficient manufacturing method for superalloy gas turbine components, *J. Manuf. Mater. Process.* 6 (5) (2022) 124.
- [25] J.D. Quadros, I. Mogul, A. Ata, I. Bedii Ozdemir, M. Mohin, Investigation of thermal characteristics of turbulent non-premixed flames in a conical bluff body using ridge and support vector regressor algorithms, *J. Therm. Sci. Eng. Appl.* 17 (4) (2025) 041002.
- [26] J.D. Quadros, Y.I. Mogul, Ü. Ağbulut, A.E. Gürel, S.A. Khan, M.N. Akhtar, R. D. Jilte, M. Asif, Analysis of bubble departure and lift-off boiling model using computational intelligence techniques and hybrid algorithms, *Int. J. Therm. Sci.* 197 (2024) 108810.
- [27] R. Sheshadri, M. Nagaraj, A. Lakshmikanthan, M.P.G. Chandrashekarappa, D. Y. Pimenov, K. Giasin, R.V.S. Prasad, S. Wojciechowski, Experimental investigation of selective laser melting parameters for higher surface quality and microhardness properties: Taguchi and super ranking concept approaches, *J. Mater. Res. Technol.* 14 (2021) 2586–2600.
- [28] T.V.K. Gupta, J. Ramkumar, P. Tandon, N.S. Vyas, Application of artificial neural networks in abrasive water jet milling, *Procedia CIRP* 37 (2015) 225–229.
- [29] J. Li, J.H. Cheng, J.Y. Shi, F. Huang, Brief introduction of back propagation (BP) neural network algorithm and its improvement, in: *Advances in computer science and information engineering*, 2, Springer Berlin Heidelberg, Berlin, Heidelberg, 2012, pp. 553–558.
- [30] A. Momeni, B. Rahmani, M. Malléjac, P. Del Hougne, R. Fleury, Backpropagation-free training of deep physical neural networks, *Science* 382 (6676) (2023) 1297–1303.
- [31] Y. Dodo, K. Arif, M. Alyami, M. Ali, T. Najeh, Y. Gamil, Estimation of compressive strength of waste concrete utilizing fly ash/slag in concrete with interpretable approaches: optimization and graphical user interface (GUI), *Sci. Rep.* 14 (1) (2024) 4598.
- [32] A. Attanasio, M. Gelfi, A. Pola, E. Ceretti, C. Giardini, Influence of material microstructures in micro milling of Ti6Al4V alloy, *Materials* 6 (2013) 4268–4283.
- [33] J. Outeiro, W. Cheng, F. Chinesta, A. Ammar, Modelling and optimization of machining of Ti-6Al-4V titanium alloy using machine learning and design of experiments methods, *J. Manuf. Mater. Process.* 6 (3) (2022) 58.
- [34] A. Pola, E. Ceretti, C. Giardini, Influence of material microstructures in micro-milling of Ti6Al4V alloy, *Materials* 6 (2013) 4268–4283.
- [35] C.A. Niranjan, S. Srinivas, M. Ramachandra, Experimental investigations on depth of penetration and surface integrity in AZ91/Al₂O₃ nanocomposites cut by abrasive water jet, *Int. J. Adv. Manuf. Technol.* 107 (2020) 747–762.
- [36] M. Jaihuni, J.K. Basak, F. Khan, F.G. Okyere, T. Sihalath, A. Bhujel, J. Park, D. H. Lee, H.T. Kim, A novel recurrent neural network approach in forecasting short term solar irradiance, *ISA Trans.* 121 (2022) 63–74.
- [37] S. Awasthi, V.K. Pal, S.K. Choudhury, Effect of surface modifications by abrasive water jet machining and electrophoretic deposition on tribological characterization of Ti6Al4V alloy, *Int. J. Adv. Manuf. Technol.* 96 (5) (2018) 1769–1777.
- [38] W.S. Abushanab, E.B. Moustafa, M. Harish, S. Shanmugan, A.H. Elsheikh, Experimental investigation on surface characteristics of Ti6Al4V alloy during abrasive water jet machining process, *Alex. Eng. J.* 61 (10) (2022) 7529–7539.
- [39] C. Chaturvedi, H. Kumar, L. Nagdeve, Machining efficiency and property change analysis of Ti-6Al-4V alloy processed by abrasive water jet machining, *J. Mater. Eng. Perform.* 34 (10) (2025) 8551–8561.
- [40] D.G. Garson. Interpreting neural network connection weights., 1991.
- [41] J.A. Hernández, W. Rivera, D. Colorado, G. Moreno-Quintanar, Optimal COP prediction of a solar intermittent refrigeration system for ice production by means of direct and inverse artificial neural networks, *Sol. Energy* 86 (4) (2012) 1108–1117.
- [42] Y.E. Hamzaoui, J.A. Hernández, S. Silva-Martínez, A. Bassam, A. Álvarez, C. Lizama-Bahena, Optimal performance of COD removal during aqueous treatment of alazine and gesaprim commercial herbicides by direct and inverse neural network, *Desalination* 277 (1–3) (2011) 325–337.
- [43] E.D. Reyes-Téllez, A. Parrales, G.E. Ramírez-Ramos, J.A. Hernández, G. Urquiza, M.I. Heredia, F.Z. Sierra, Analysis of transfer functions and normalizations in an ANN model that predicts the transport of energy in a parabolic trough solar collector, *Desalin. Water Treat.* 200 (2020) 23–41.
- [44] A.T. Goh, Back-propagation neural networks for modeling complex systems, *Artif. Intell. Eng.* 9 (3) (1995) 143–151.