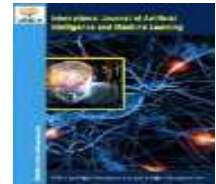




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Research Paper

A Comparative Analysis of Regression Coefficient, Mse and Mape for Abrasive Slotting Machine

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Abstract

This study presents an experimental investigation on abrasive air jet machining on alumina reinforced with zirconium composite materials. The aim is to optimize the machining process parameters using a Taguchi and neural network techniques. The experiment was designed based on the L27 orthogonal array of the Taguchi method, considering four input parameters: pressure, abrasive flow rate, stand-off distance and type of materials. The response variables, material removal rate, and surface roughness were measured and analyzed. Regression analysis was performed to evaluate the goodness of fit (R^2) between experimental and predicted values. Additionally, Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE) were calculated to assess the accuracy of predictions using both Taguchi and neural network models. The combined approach of Taguchi and neural network techniques offers a robust method for optimizing abrasive air jet machining parameters for alumina-zirconium composites. The findings provide valuable insights for enhancing machining efficiency and surface quality in various industrial applications

Keyword: Abrasive Slotting Machine, Ceramic Composites, Regression, ANN, MSE, MAPE

Introduction

Ceramic materials are applied in material science, electrical, chemical, and mechanical engineering to resist high temperature. These materials used in a wide range of industries such as mining, aerospace, medicine [1], refining, the base of the floodlights, ball bearings, fuse bodies, chemistry, packaging science, electronics, transmission and industrial electricity, and guided light wave transmission [2][3]. Aluminum oxide is currently the world's second material after iron. Aluminum has a rare desired combination of properties such as light weight, high strength, easy machining, excellent corrosion resistance and high thermal and electrical conductivity [8] [9] In this research work, zirconium nano powder particles are used as a reinforcement material, it is exceptional mechanical properties [12] such as strength, hardness, and wear resistance etc. [13][14][15].

LITERATURE REVIEW

Ceramic materials have emerged as critical components in various branches of engineering including material science, electrical, chemical, and mechanical engineering, primarily due to their ability to resist high temperatures. Their applications span across numerous industries, ranging from mining, aerospace, and medicine to refining, electronics and industrial electricity. According to previous studies [1] ceramic materials are pivotal in fields requiring durability and performance in extreme conditions. ceramics are widely used in ball bearings, fuse bodies, and floodlight bases, demonstrating their versatile mechanical and thermal properties. Moreover, they are also integral to packaging science and guided light wave transmission, enhancing the efficiency of modern electronics and industrial systems [2][3].

Among ceramic materials, aluminum oxide stands out as the second most widely used material globally, following iron. Aluminum oxide's popularity stems from its unique set of properties, including its lightweight nature, high strength, excellent machinability, superior corrosion resistance, and exceptional thermal and electrical

conductivity [8][9]. These properties have made aluminum an essential material in applications ranging from construction to high-tech electronic devices, emphasizing its versatility and economic significance.

In recent years, there has been increasing interest in reinforcing ceramic matrices with nano-particles to further enhance their mechanical properties. Zirconium nano-powder particles, in particular, have gained attention due to their exceptional mechanical characteristics. Zirconium's incorporation as a reinforcement material has been noted for significantly improving the strength, hardness, and wear resistance of composites, making it an ideal candidate for high-performance engineering applications [16][17]. Studies have shown that zirconium nano-reinforcements can extend the service life and enhance the reliability of components exposed to extreme mechanical and thermal stresses, making them highly valuable in industries such as aerospace and automotive manufacturing.

2.0 Materials And Methods

Improperly chosen material can cause component failure and unnecessary life cycle costs. Choosing the best material for a part involves more than choosing a material that has the properties to deliver the required performance in service [4][18] it is also closely linked to the processing of the material into finished parts. Poorly chosen material can increase production costs and unnecessarily increase the cost of the finished product [5][17]. In addition, the properties of the material may be improved or reduced by processing, which may affect the performance of the product. In this research work, ceramics composites (5wt. %, 10wt. % and 15wt. %) are produced by powder metallurgy sintering method [19]. Ceramic composites before and after machining as shown in fig. 1 and fig.3 respectively.

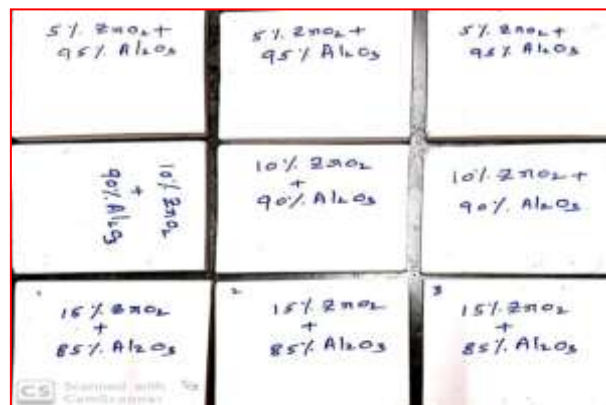


Fig. 1 Composite materials before machining

2.1 MACHINING

Abrasive Air Jet Machine as shown in fig. 2 involves impinging of fine abrasive particles on the work piece material at a very high velocity causing a small fracture on the work piece surface on impact shown. In this research work silicon carbide (SiC) abrasive particles have impinged on the work piece targeted surface[18][20] Abrasive air jet machine is used for drilling and grinding thin brittle materials, debarring, etching and cleaning hard and brittle materials.



Fig. 2 Abrasive air jet setup

Table: 1 Process Parameters and their levels

			Levels		
Process parameters	Units	Notation	1	2	3
Pressure	bar	P	6	8	10
Abrasive flow rate	gm/min	AFR	10	15	20
Standoff Distance	mm	SOD	5	10	15
Type of sample	% of ZrO ₂	M	5%	10%	15%

2.2 OBSERVATIONS

Material Removing Rate (MRR):

The process parameters, units and their levels as shown in table 1. The material removal rate is determined using the weight method, measure the weight of the work piece before machining

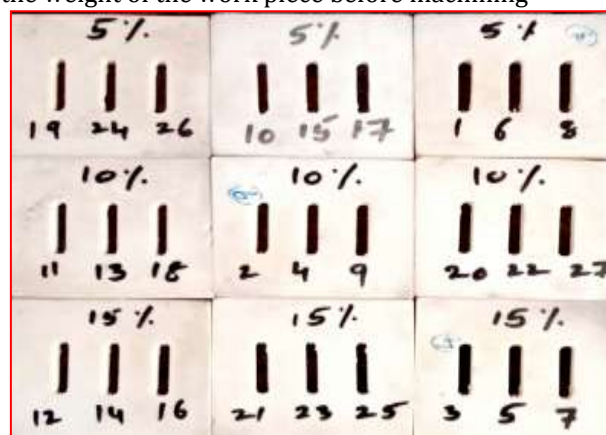


Fig: 3 Composites after machining

Surface Roughness

Surface roughness is one of the best quality control outputs to ensure that the functional surfaces of manufactured parts meet specified standards. Surface roughness is an important factor in monitoring the production process and quality control. In this research, MITUTOYO SJ-210 tester is used to measure surface roughness of ceramic composite samples as shown in fig. 4



Fig: 4 Surface Roughness Tester

2.3 EXPERIMENTATION

Table 2: Measure MRR and Surface Roughness

Exp No.	Pressure (bar)	AFR (gm/min)	SOD (mm)	Sample (% of Reinforcement)	MRR (gm/min)	Ra (μm)
1	6	10	5	5	1.730	8.210
2	6	10	10	10	1.970	6.950
3	6	10	15	15	1.490	7.010
4	6	15	5	10	2.190	6.970
5	6	15	10	15	2.114	6.550
6	6	15	15	5	1.696	7.930

7	6	20	5	15	1.926	6.220
8	6	20	10	5	1.912	6.730
9	6	20	15	10	1.490	6.930
10	8	10	5	5	1.850	8.650
11	8	10	10	10	2.092	8.450
12	8	10	15	15	2.395	6.446
13	8	15	5	10	2.264	7.350
14	8	15	10	15	2.064	7.400
15	8	15	15	5	1.724	7.920
16	8	20	5	15	2.286	6.420
17	8	20	10	5	1.972	6.520
18	8	20	15	10	1.978	6.920
19	10	10	5	5	2.272	8.710
20	10	10	10	10	2.432	8.760
21	10	10	15	15	2.102	7.670
22	10	15	5	10	2.428	7.580
23	10	15	10	15	2.872	7.670
24	10	15	15	5	2.450	7.620
25	10	20	5	15	2.752	6.570
26	10	20	10	5	2.736	6.990
27	10	20	15	10	2.323	7.990

3 RESULTS AND DISCUSSION:

Table 3: MRR Measured, Predicted and their Residuals and MSE

Exp No.	Pressure (bar)	AFR (g/min)	SOD (mm)	Material (% of ZrO ₂)	MRR (Measured) (gm/min)	MRR (Prediction) (gm/min)	Residual	Residual Square	MAPE (%)
1	6	10	5	5	1.73	1.709	0.021	0.000441	1.2
2	6	10	10	10	1.97	1.852	0.118	0.013924	6
3	6	10	15	15	1.49	1.666	-0.176	0.030976	11.8
4	6	15	5	10	2.19	1.964	0.226	0.051076	10.3
5	6	15	10	15	2.114	2.108	0.006	3.6E-05	0.3
6	6	15	15	5	1.696	1.644	0.052	0.002704	3.1
7	6	20	5	15	1.926	2.009	-0.083	0.006889	4.3
8	6	20	10	5	1.912	1.877	0.035	0.001225	1.8
9	6	20	15	10	1.49	1.689	-0.199	0.039601	13.4
10	8	10	5	5	1.85	1.943	-0.093	0.008649	5
11	8	10	10	10	2.092	2.087	0.005	2.5E-05	0.2
12	8	10	15	15	2.395	1.900	0.495	0.245025	20.7
13	8	15	5	10	2.264	2.198	0.066	0.004356	2.9
14	8	15	10	15	2.064	2.342	-0.278	0.077284	13.5
15	8	15	15	5	1.724	1.879	-0.155	0.024025	9
16	8	20	5	15	2.286	2.243	0.043	0.001849	1.9
17	8	20	10	5	1.972	2.111	-0.139	0.019321	7
18	8	20	15	10	1.978	1.923	0.055	0.003025	2.8
19	10	10	5	5	2.272	2.359	-0.087	0.007569	3.8
20	10	10	10	10	2.432	2.502	-0.07	0.0049	2.9
21	10	10	15	15	2.102	2.315	-0.213	0.045369	10.1
22	10	15	5	10	2.428	2.614	-0.186	0.034596	7.7
23	10	15	10	15	2.872	2.758	0.114	0.012996	4
24	10	15	15	5	2.45	2.294	0.156	0.024336	6.4
25	10	20	5	15	2.752	2.659	0.093	0.008649	3.4
26	10	20	10	5	2.736	2.526	0.21	0.0441	7.7
27	10	20	15	10	2.323	2.339	-0.016	0.000256	0.7

Measured material removing rate and prediction values as shown in table 3, The Mean Square Error values (MSE) and Mean Absolute Percentage Error (MAPE) of Surface roughness are 0.0264 and 5.99% respectively. Fig.5 shows that the relationship between measured and prediction values of material removing rate the experimental values are close to prediction values so fit is good agreement between experimental and predicted.

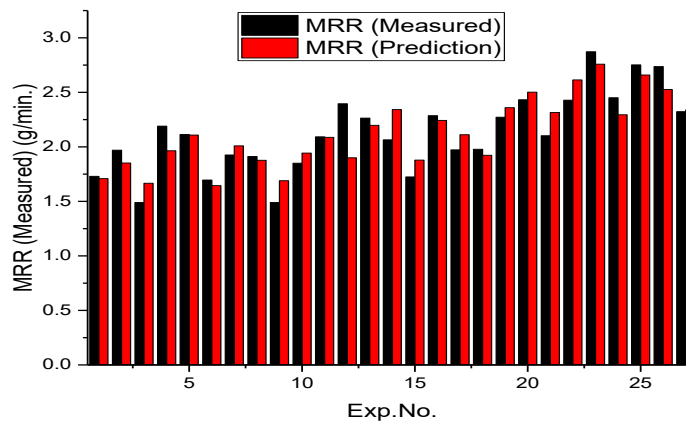


Fig 5. Experimental and predicted values of MRR

Table 4: Experimental and Predicted Values of Surface roughness and their Residuals and MSE by Regression

Exp No.	Pressure (bar)	AFR (gm/min)	SOD (mm)	Material (% of ZrO ₂)	Surface Roughness (Measured) (μm)	Surface Roughness (Prediction) (μm)	Residual	Residual Square	MAPE (%)
1	6	10	5	5	8.21	8.180	0.030	0.0009	0.4
2	6	10	10	10	6.95	6.870	0.080	0.0064	1.2
3	6	10	15	15	7.01	7.068	-0.058	0.0033	0.8
4	6	15	5	10	6.97	7.126	-0.156	0.0243	2.2
5	6	15	10	15	6.55	6.592	-0.042	0.0017	0.6
6	6	15	15	5	7.93	7.860	0.070	0.0049	0.9
7	6	20	5	15	6.22	6.032	0.187	0.0352	3
8	6	20	10	5	6.73	6.773	-0.042	0.0018	0.6
9	6	20	15	10	6.93	6.666	0.264	0.0699	3.8
10	8	10	5	5	8.65	8.195	0.454	0.2069	5.3
11	8	10	10	10	8.45	8.420	0.030	0.0009	0.4
12	8	10	15	15	6.446	6.356	0.090	0.0081	1.4
13	8	15	5	10	7.35	7.480	-0.130	0.0169	1.8
14	8	15	10	15	7.4	7.360	0.040	0.0016	0.5
15	8	15	15	5	7.92	7.738	0.181	0.0329	2.3
16	8	20	5	15	6.42	6.318	0.101	0.0103	1.6
17	8	20	10	5	6.52	6.880	-0.36	0.1296	5.5
18	8	20	15	10	6.92	6.952	-0.031	0.0010	0.5
19	10	10	5	5	8.71	8.682	0.028	0.0007	0.3
20	10	10	10	10	8.76	8.756	0.004	1.6E-05	0.01
21	10	10	15	15	7.67	7.741	-0.071	0.0050	0.9
22	10	15	5	10	7.58	7.999	-0.419	0.1758	5.5
23	10	15	10	15	7.67	7.266	0.4044	0.1635	5.3
24	10	15	15	5	7.62	8.126	-0.505	0.2555	6.6
25	10	20	5	15	6.57	6.706	-0.135	0.0183	2.1
26	10	20	10	5	6.99	7.446	-0.456	0.2079	6.5
27	10	20	15	10	7.99	7.339	0.6511	0.4239	8.1

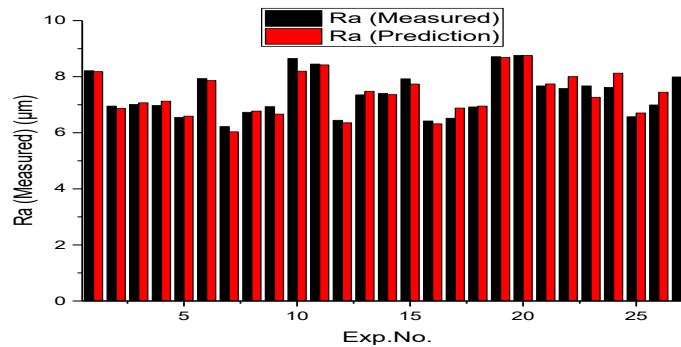


Fig. 6. Experimental and predicted values of surface roughness

Measured surface roughness and prediction values as shown in table 4. The Mean Square Error values (MSE) and Mean Absolute Percentage Error (MAPE) of Surface roughness are 0.066 and 2.522 % respectively. Fig.6 shows that the relationship between measured and prediction values, the experimental values are close to prediction values so fit were good and agreement between experimental and predicted values also good.

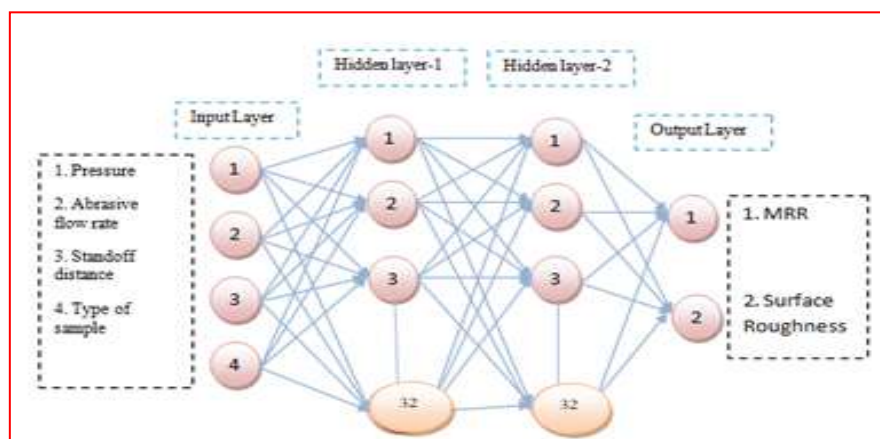


Fig 7: Schematic illustration of the neural network model

Neural Network Design and Training

The ability to generalize the neural network mainly depends on 1 selecting the appropriate input / output parameters of the system; (ii) dissemination of the data set; and (iii) the network representation format of the data set. In this study, the total number of experimental results is 27 datasets, of which 18 (two-thirds) were taken into account for training and 9 for testing. The input / output data set is normalized to ± 1 before network training. The standard multilayer back propagation neural network is developed in the MATLAB15 neural network toolkit. The network consists of three layers: input, hidden and output. The currently developed network has four input neurons and two output neurons.

The Artificial Neural Networks (ANN) model is used to predict the material removal and surface roughness of ceramic composites. The input parameters are pressure (P), Abrasive Flow Rate (AFR), Standoff Distance (SOD) and Sample Type (M). These are taken into account to predict the responses. The data is taken from the experimental results. ANN Information has a training function is TRAINLM, a learning function is LEARNM and the transfer function is TRAINSIG. This work was done by using MATLAB 2014.

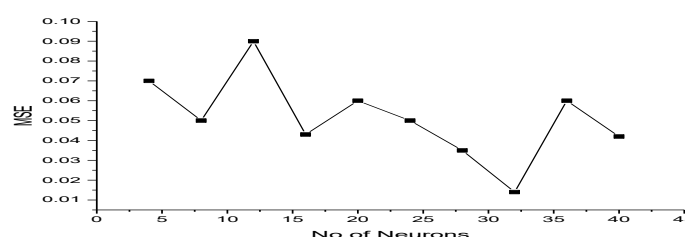


Fig 8: Performance of single-layer network with varying neurons

Fig 8. observed that the lowest average MSE (0.014) is obtained at 32 neurons in a single hidden layer. The network is again trained with varying neurons in a double hidden layer. In contrast, a single hidden is fixed with 32 neurons. It is also observed that the MSE obtained by the single-layer network with 32 neurons is lower than the lowest MSE obtained from double hidden layer network with varying neurons. A single hidden layer (4-32-2) ANN architecture with back propagation algorithm has been selected for modelling of the process parameters on micro abrasive air-jet machining. The developed (4-32-2). The learning behaviour of the network and convergence of MSE with every epoch during the training period. The synaptic weight and bias of the network are stored and assigned with (4-32-2). The MSE, R^2 and MAPE Values in the ANN model of MRR are 0.0097, 98.88%, and 2.566%. The MSE, R^2 and MAPE Values in the ANN model of Surface Roughness are 0.0043, 98.88%, and 1.59%. The Experimental and predicted values of MRR and Ra are summarized in table 5.33. The comparison between experimental and predicted values of MRR and Ra through graphical representation as shown in fig. 5.69 & 5.70 respectively.

Table 5: Experimental and Predicted Values of MRR and Ra by ANN model

Exp No.	Pressure (bar)	AFR (gm/min)	SOD (mm)	Material (% of ZrO ₂)	MRR (Measured) (gm/min)	MRR (Prediction) (g/min)	Ra Measured (μm)	Ra (Prediction) (μm)
1	6	10	5	5	1.73	1.704	8.21	8.19
2	6	10	10	10	1.97	1.983	6.95	6.90
3	6	10	15	15	1.49	1.709	7.01	7.02
4	6	15	5	10	2.19	1.805	6.97	6.88
5	6	15	10	15	2.114	2.102	6.55	5.58
6	6	15	15	5	1.696	1.714	7.93	7.95
7	6	20	5	15	1.926	1.921	6.22	6.18
8	6	20	10	5	1.912	1.913	6.73	6.65
9	6	20	15	10	1.49	1.534	6.93	6.88
10	8	10	5	5	1.85	1.868	8.65	8.55
11	8	10	10	10	2.092	2.097	8.45	8.38
12	8	10	15	15	2.395	2.350	6.446	6.56
13	8	15	5	10	2.264	2.259	7.35	7.32
14	8	15	10	15	2.064	2.076	7.4	7.32
15	8	15	15	5	1.724	1.794	7.92	8.02
16	8	20	5	15	2.286	2.136	6.42	6.44
17	8	20	10	5	1.972	1.959	6.52	6.67
18	8	20	15	10	1.978	1.969	6.92	6.72
19	10	10	5	5	2.272	2.313	8.71	8.62
20	10	10	10	10	2.432	2.545	8.76	8.68
21	10	10	15	15	2.102	2.112	7.67	7.77
22	10	15	5	10	2.428	2.434	7.58	7.48
23	10	15	10	15	2.872	2.849	7.67	7.57
24	10	15	15	5	2.45	2.580	7.62	7.68
25	10	20	5	15	2.752	2.752	6.57	6.59
26	10	20	10	5	2.736	2.764	6.99	7.18
27	10	20	15	10	2.323	2.335	7.99	7.88

Table 6: Comparison of residual, MSE and MAPE of Regression and ANN model on MRR

Exp.No	Measured MRR (gm/min.)	Regression				Artificial Neural Network			
		Prediction MRR (g/min.)	Residual	(Resi.) ²	Abs.% error	Prediction MRR (gm/min.)	Residual	(Resi.) ²	Abs.% error
1	1.73	1.709	0.021	0.00044	1.2	1.704	0.026	0.0006	1.5
2	1.97	1.852	0.118	0.01392	6	1.983	-0.013	0.0001	0.7
3	1.49	1.666	-0.176	0.03097	11.8	1.709	-0.219	0.0480	14.7
4	2.19	1.964	0.226	0.05107	10.3	1.805	0.385	0.1484	17.6
5	2.114	2.108	0.006	3.6E-05	0.3	2.102	0.012	0.0001	0.6
6	1.696	1.644	0.052	0.00270	3.1	1.714	-0.018	0.0003	1.1
7	1.926	2.009	-0.083	0.00688	4.3	1.921	0.005	2.1E-05	0.2
8	1.912	1.877	0.035	0.00122	1.8	1.913	-0.001	1.7E-06	0.1
9	1.49	1.689	-0.199	0.03960	13.4	1.534	-0.044	0.0019	2.9
10	1.85	1.943	-0.093	0.00864	5	1.868	-0.018	0.0003	1
11	2.092	2.087	0.005	2.5E-05	0.2	2.097	-0.005	2.0E-05	0.2
12	2.395	1.9	0.495	0.24502	20.7	2.350	0.045	0.0020	1.9
13	2.264	2.198	0.066	0.00435	2.9	2.259	0.005	2.3E-05	0.2
14	2.064	2.342	-0.278	0.07728	13.5	2.076	-0.012	0.0001	0.6
15	1.724	1.879	-0.155	0.02402	9	1.794	-0.070	0.0049	4.1
16	2.286	2.243	0.043	0.00184	1.9	2.136	0.150	0.0224	6.6
17	1.972	2.111	-0.139	0.01932	7	1.959	0.013	0.0001	0.7
18	1.978	1.923	0.055	0.00302	2.8	1.969	0.009	7.9E-05	0.4
19	2.272	2.359	-0.087	0.00756	3.8	2.313	-0.041	0.0016	1.8
20	2.432	2.502	-0.07	0.0049	2.9	2.545	-0.113	0.0127	4.6
21	2.102	2.315	-0.213	0.04536	10.1	2.112	-0.010	0.0001	0.5
22	2.428	2.614	-0.186	0.03459	7.7	2.434	-0.006	3.0E-05	0.2
23	2.872	2.758	0.114	0.01299	4	2.849	0.023	0.0005	0.8
24	2.45	2.294	0.156	0.02433	6.4	2.580	-0.130	0.0169	5.3
25	2.752	2.659	0.093	0.00864	3.4	2.752	0.000	1.2E-07	0
26	2.736	2.526	0.21	0.0441	7.7	2.764	-0.028	0.0007	1
27	2.323	2.339	-0.016	0.00025	0.7	2.335	-0.012	0.0001	0.5

Table 7: Comparison of residual, MSE and MAPE by Regression and ANN model on Ra

Exp.No	Measured Ra (μm)	Regression				Artificial Neural Network			
		Prediction Ra(μm)	Residual	(Resi.) ²	Abs.% error	Prediction Ra(μm)	Residual	(Resi.) ²	Abs.% error
1	8.21	8.180	0.0300	0.0009	0.4	8.19	0.02	0.0004	0.2
2	6.95	6.870	0.0800	0.0064	1.2	6.90	0.05	0.0025	0.7
3	7.01	7.068	-0.0580	0.0033	0.8	7.02	-0.01	0.00013	0.2
4	6.97	7.126	-0.156	0.0243	2.2	6.88	0.09	0.0081	1.3
5	6.55	6.592	-0.0422	0.0017	0.6	5.58	0.97	0.9409	14.8
6	7.93	7.860	0.0700	0.0049	0.9	7.95	-0.02	0.0004	0.3
7	6.22	6.032	0.18777	0.0352	3	6.18	0.04	0.0016	0.6
8	6.73	6.773	-0.0426	0.0018	0.6	6.65	0.08	0.0064	1.2
9	6.93	6.666	0.2644	0.0699	3.8	6.88	0.05	0.0025	0.7
10	8.65	8.195	0.45488	0.2069	5.3	8.55	0.10	0.0100	1.2
11	8.45	8.420	0.0300	0.0009	0.4	8.38	0.07	0.0049	0.8
12	6.44	6.356	0.0900	0.0081	1.4	6.56	-0.12	0.0139	1.8
13	7.35	7.480	-0.1300	0.0169	1.8	7.32	0.03	0.0009	0.4
14	7.4	7.360	0.0400	0.0016	0.5	7.32	0.08	0.0064	1.1
15	7.92	7.738	0.18155	0.0329	2.3	8.02	-0.10	0.0100	1.3
16	6.42	6.318	0.10155	0.0103	1.6	6.44	-0.02	0.0004	0.3
17	6.52	6.880	-0.3600	0.1296	5.5	6.67	-0.15	0.0225	2.3
18	6.92	6.952	-0.0317	0.0010	0.5	6.72	0.20	0.040	2.9
19	8.71	8.682	0.028	0.0007	0.3	8.62	0.09	0.0081	1
20	8.76	8.756	0.004	1.6E-05	0	8.68	0.08	0.0064	0.9
21	7.67	7.741	-0.0713	0.0050	0.9	7.77	-0.10	0.0100	1.3
22	7.58	7.999	-0.4193	0.1758	5.5	7.48	0.10	0.0100	1.3
23	7.67	7.266	0.40444	0.1635	5.3	7.57	0.10	0.0100	1.3

24	7.62	8.126	-0.5055	0.2555	6.6	7.68	-0.06	0.0030	0.8
25	6.57	6.706	-0.1355	0.0183	2.1	6.59	-0.02	0.0004	0.3
26	6.99	7.446	-0.456	0.2079	6.5	7.18	-0.19	0.0361	2.7
27	7.99	7.339	0.6511	0.4239	8.1	7.88	0.11	0.0121	1.4

Residual = (Measure values – Prediction Values)

Mean Square Error (MSE) = $\frac{\text{Sum of Residual square}}{N}$

Absolute percentage error = $\frac{| \text{Residual} |}{\text{Measured Value}}$

Mean absolute percentage error (MAPE) = $\frac{\text{Sum of absolute \% error}}{N} * 100$

N= No. of Experiments

The study focuses on fine-tuning the machining Parameters by using a combination of Taguchi method and neural network techniques to achieve better performance in terms of material removal rate (MRR) and surface roughness (Ra). Where AAJM is applied to alumina zirconium composites using various machining parameters pressure, abrasive flow rate, stand-off distance and material type. These parameters are arranged according to an L_{27} orthogonal array based on the Taguchi method ensuring that a wide range of combinations is tested with minimal experiments.

During the process the response variables (MRR and surface roughness) are recorded. The data collected is then used to train a neural network model to predict outcomes under different conditions. Regression analysis, MAPE, and MSE are employed to measure the accuracy of these predictions. By integrating the Taguchi approach with neural networks, the study ensures both experimental efficiency and predictive precision.

This combined methodology enables the identification of optimal process parameters, helping industries improve machining efficiency and surface quality when working with complex composite materials like alumina-zirconium.

4. CONCLUSION

The performance of both the Regression and Artificial Neural Network (ANN) models in predicting the material removal rate (MRR) and surface roughness (Ra) was evaluated. For the Regression model, the variance (R^2), mean square error (MSE), and mean absolute percent error (MAPE) for MRR were 94.54%, 0.0264, and 5.99%, respectively. In terms of surface roughness, the Regression model had a variance (R^2) of 92.32%, an MSE of 0.066, and a MAPE of 2.522%. Comparisons between the experimental data and the ANN model predictions showed a good agreement, demonstrating the effectiveness of the ANN in modelling these parameters. The ANN model showed superior performance with an R^2 of 98.88%, an MSE of 0.0097, and a MAPE of 2.566% for MRR, and for surface roughness, the values were R^2 of 98.88%, MSE of 0.0043, and MAPE of 1.59%. These results indicate that the ANN model offers a more precise method for determining MRR and Ra compared to the Regression model.

Hence it may be concluded that the machining optimization parameters given by ANN are close to experimental parameters compare to Regression model hence it is recommended to use the technique for machining of developed ceramic matrix composites to reduce the machining time, improve accuracy with good surface finish.

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