"An Artificial Neural Network Approach to Investigate Surface Roughness of Al 8011 and Nano Zro_2 Composites in CNC Turning Process"

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ABSTRACT
In order to maximize surface roughness (Ra), this Research looks at converting composites made of nano ZrO_2 and aluminum 8011 alloys. Machining parameters of speed (500, 1000, 1500 rev/min), feed (0.1, 0.2, 0.3 mm/rev), and depth of cut (0.5, 1.0, 1.5) were used in L_{27} Taguchi's orthogonal tests.A mathematical Surface Roughness (Ra) model has been established for the CNC turning process utilizing an Artificial Neural Network (ANN) model. When utilizing an artificial neural network model, a deviation of 1.89% errors is observed for Ra. The variance of the ANN-predicted and experimental findings is within the allowable range. The ANN model showed better forecasting ability.

Keywords: Al 8011,Nano ZrO_2,Artificial Neural Network, Surface Roughness

1. INTRODUCTION

Composite materials are cutting-edge and versatile in the engineering material world. These composite materials are considered exciting and spectacular due to scientific and technological advancements (Mohammad et al., 2021; Sunil Kumar M et al., 2021).

Composites were developed due to materials science studies that sought lighter alternatives to heavy materials. Metal matrix composites may have their attributes enhanced to the point where they surpass monolithic alloys concerning high-temperature performance, creep resistance, fatigue resistance, specific strength, rigidity, and improved thermal and mechanical characteristics. The sources used are Laghari et al. (2018) and Umer et al. (2022).

Many industries, including transportation, aircraft, and locomotives, use particulate-reinforced aluminum composites because of their increased strength and hardness. "Incorporating second-phase nanoparticles into a base matrix has allowed nanocomposites to greatly enhance mechanical strength, creep resistance, and fatigue life without compromising the ductile characteristics of the matrix, which has led to their increasing popularity in the last decade." (Niu, Z., et al., 2021; Senthil raj, et al., 2022). "The machinability of composites is affected by the hardness of the reinforcements and differs from that of the matrix material, which is an intrinsic aspect of the manufacturing process". Therefore, the importance of machinability studies in composites Research has increased (Devaraj et al., 2021).

The three input parameters—feed rate, DOC, and cutting speed—for turning, the most essential and desired metal removal operation in machining, have been appropriately adjusted in earlier studies to provide satisfactory outcomes. (Kesarwani et al., 2022 and Prakash et al., 2022).

CNC is rapidly becoming an integral part of many industries. Traditional techniques are unable to produce the same level of precision, surface quality, and accuracy (dimensionally) as CNC (Balasubramanian et al., 2019).

Machine components significantly affect aesthetics, corrosion resistance, fatigue strength, and surface roughness (Ra). Consequently, Ra is an essential production measure (Hiba K. Hussein et al., 2019).

The impact of surface roughness on component machining and manufacturing costs makes it a crucial quality parameter. The primary need is the surface factor, followed by geometric and dimensional characteristics. (Putnam, et al., 2021).

The effect of feed rate, cutting depth, and cutting speed on the toughness and power of an aluminum alloy's surface upon longitudinal turning. “An Artificial Neural Network (ANN) and a Response Surface Methodology (RSM) were used to analyze experimental data for response prediction." Research shows that when compared to the RSM, the ANN is a stronger predictor of surface roughness. (Aljinovic, Amanda, et al., 2021)
Machined AA6061 alloy with carbide cutting tools: developing predictive and numerical models of surface roughness parameter (Ra). “To construct these models, we evaluated cutting speed, depth of cut, and feed rate.” According to Aykut Eser et al. (2021), the classic backpropagation strategy is the most effective method for training an ANN model.
The input parameters for machining AISI 1040 hardened mild steels with coated carbides were speed, feed, and depth of cut, which were examined by Yusuf Şahin (2023). “We compare and project these results using response surface methodology (RSM) and artificial neural networks (ANN).” The results demonstrate that ANN outperforms RSM regarding prediction accuracy and speed. “The present investigation aims to ascertain the effect of various machining input parameters on C40 steel output, as evaluated by surface roughness and metal removal rate (MRR), by analyzing the relationships between cutting speed, feed rate, depth of cut, and nose radius, A model was created utilizing experimental data and computer numerical control (CNC) turning parameters to forecast surface roughness and material removal rate (MRR) during the turning operation using artificial neural network (ANN) technology.” Results show that anticipated and measured values are somewhat in the same ballpark (Saadat Ali Rizvi and Wajahat Ali 2021)
The titanium alloy Ti-6Al-4 V alloy is milled on a programmed CNC lathe using a coated carbide tool in this work. “Machine learning technology ANN is used to forecast the rate of material removal and surface roughness, while RSM is used to optimize the cutting parameters.” The artificial neural network has a surface roughness of 5.04% and an MRR error rate of 10.66%. The ANN's % error numbers are much lower than RSM's. Predicting surface roughness has lately attracted the attention of the machining industry (Mulugundam Siva Surya, et al., 2021). “This research used cutting speed, feed, and depth of cut to predict the surface roughness of the hardened steel; using regression techniques and a model of an artificial neural network, surface roughness might be predicted.” The results demonstrated that the artificial neural network outperformed the regression model in predicting surface roughness. Ajay Vasanth et al. (2021)
To predict surface roughness in Inconel 718 turning, an artificial neural network method is used in conjunction with cutting parameters, force, vibration, and sound. “An artificial neural network can forecast surface roughness with a precision of above 98%.” The revised regression models achieved an accuracy of above 90% when estimating surface roughness. “Results show that ANN models are more accurate than regression approaches in predicting surface roughness, which helps control the real-time process to get the desired surface roughness.” It was published by (Ajay Vasanth et al., 2021), "The experimental investigation and prediction of surface roughness in a rotating SiC-Al alloy composite were carried out using an artificial neural network (ANN) and an adaptive neuro-fuzzy inference system (ANFIS).” According to the results, surface roughness is drastically reduced using the back-propagation approach. (Et al., Rezaul Karim, 2018).
This study aims to synthesize three distinct Al8011 and nano zro2 samples reinforced with 2%,4%, and 6% by weight. Although the benefits of AL alloys have been discussed before, reducing surface roughness during machining is a challenge. Nevertheless, machinability may be significantly enhanced with the correct input parameters. We used Taguchi's orthogonal array to conduct our experiments. “Several process factors are used to evaluate the produced composites' surface roughness.” A quantitative assessment of the anticipated and experimental surface roughness values was carried out using the Artificial Neural Network.

2. Materials and Procedures

Recent developments in composites that include microparticles have improved output responses. "Several factors, including cutting speed, feed rate, depth of cut, and the weight percent of nanoparticles used as reinforcement, affect the surface roughness of the produced composites.”

2.1. Materials and Characteristics

One such matrix material is Al 8011, an alloy of silicon and iron. Its lightweight design, corrosion resistance, and simplicity of product maintenance are some of its benefits. There is a 237 W/mk thermal conductivity and a 2.71 g/cm3 density. The material Al 8011 is marketed in sheet form. “Table 1 shows the chemical composition of Al 8011 as per the International Alloy Designations”.

Table 1: Al 8011's composition in chemical terms

Chemical Structure	Si	Fe	Cu	Mn	Mg	Cr	Zn	Ti	Al
composition in wt.%	0.5	0.6	0.1	0.2	0.05	0.05	0.1	0.08	rest

The chemical resistance, great strength, unusual stability, and brilliant natural color of nano ZrO2 make it a significant scientific material. Nanoparticles of zirconium oxide may take a few different forms: dots, fluids, and particles.

2.2Manufacturing of composites

This study examined the effects of stir-casting Al 8011 with varying percentages of nano ZrO2 reinforcement (2, 4, and 6%). Nano ZrO2 particles were heated with Al 8011 and weighed in an electronic weighing machine to enhance wettability. A graphite crucible containing the required quantities of Al 8011 alloy was heated to about 90050° C in an induction furnace. “Gravity, meanwhile, draws in microscopic ZrO2 particles. A stainless-steel impeller with three blades was used to stir for 10 minutes at 300 rpm, Two hexachloroethane tablets are added to the mixture to remove any gas.” Mechanical churning creates A vortex in the melt, which evenly distributes the reinforcing particles throughout the matrix. In order to make castings of superior quality, the slag that builds up at the vortex's apex is removed. “After removing the crucible from the furnace, the combination of scalding liquids is carefully poured into a preheated cast-iron mold; after cooling, composites of varying compositions were CNC turned, as shown in Figure 1 (a).”

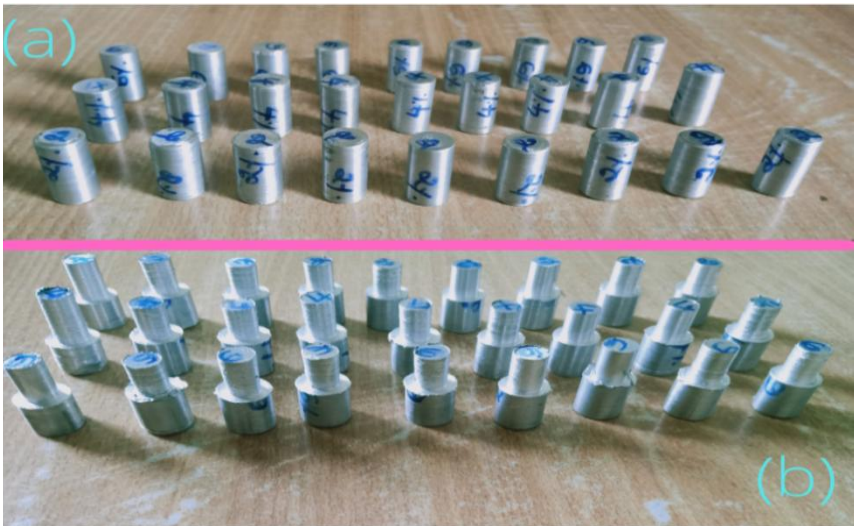

Fig 1 (a): made-up composites **Fig 1(b):** composites after CNC turning

2.3 Taguchi experiments and CNC turning

For this test, we employed a 3-, 4-, and 6-percent Al 8011 specimen composited with nano ZrO2. It measured 15 mm by 30 mm. Figure 2 shows the wholly automated HAAS CNC Lathe used for milling samples. An environment free of moisture was used to conduct the experiments. Utilizing coated carbide insert material, a cutting tool is created. The specimens that have been CNC-turned are shown in Figure 1 (b). “Mitutoyo SJ-201P, as illustrated in Fig.3, was used to measure surface roughness over a (2.5 cm) sample length.” By decreasing the number of experiments and the impact of uncontrolled factors, the Taguchi method seeks to improve Research. Designing with quality in mind is vital to the Taguchi method. The Taguchi method offers the best benefits in rapidly reducing trial time and costs and locating relevant components. The experimental process parameters, including the ZrO2 weight %, speed, feed, depth of cut, and feeding levels, are shown in Table 2. “The surface roughness values for 27 trials are included in Table 3, which shows that the L27 orthogonal array was employed to perform tests for various process parameters.”

Table 2: Process variables and levels of feeding

Sl no	Symbol	Input parameters	Units	Levels		
				1	**2**	**3**
1	A	Weight percent of ZrO_2	%	2	4	6
2	B	Speed	rpm	500	1000	1500
3	C	Feed	mm/rev	0.1	0.2	0.3
4	D	Depth of Cut	mm	0.2	0.4	0.6

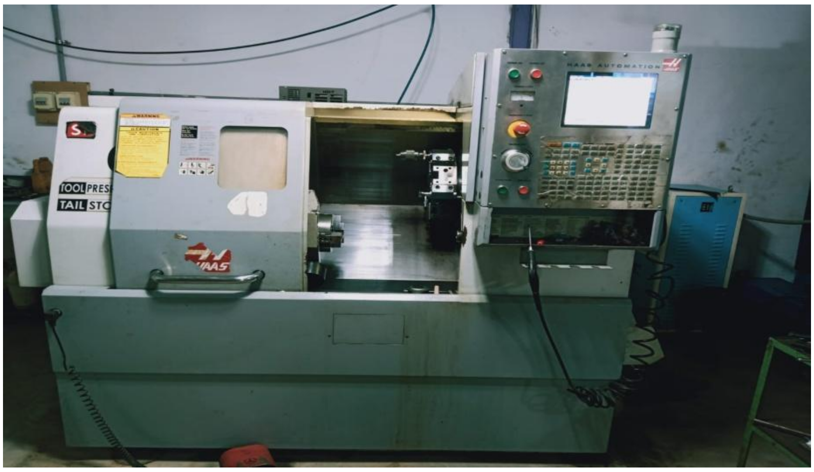

Fig 2: Automated HAAS CNC Lathe

Fig 3: Surf Tester

Table 3: Results of L27 orthogonal array experiments

Trail no	Reinforcement in %	Speed in rpm	Feed in mm/rev	Depth of cut in mm	Surface roughness in micron meter
1	2	500	0.1	0.2	2.871
2	2	500	0.2	0.4	3.384
3	2	500	0.3	0.6	4.084
4	2	1000	0.1	0.4	2.802
5	2	1000	0.2	0.6	2.115
6	2	1000	0.3	0.2	4.425
7	2	1500	0.1	0.6	2.2561
8	2	1500	0.2	0.2	3.2461
9	2	1500	0.3	0.4	4.3461

10	4	500	0.1	0.4	1.864
11	4	500	0.2	0.6	2.964
12	4	500	0.3	0.2	4.464
13	4	1000	0.1	0.6	1.636
14	4	1000	0.2	0.2	3.336
15	4	1000	0.3	0.4	4.436
16	4	1500	0.1	0.2	1.998
17	4	1500	0.2	0.4	2.478
18	4	1500	0.3	0.6	2.178
19	6	500	0.1	0.6	1.831
20	6	500	0.2	0.2	3.331
21	6	500	0.3	0.4	4.43
22	6	1000	0.1	0.2	2.14
23	6	1000	0.2	0.4	3.64
24	6	1000	0.3	0.6	1.978
25	6	1500	0.1	0.4	1.945
26	6	1500	0.2	0.6	3.18672
27	6	1500	0.3	0.2	4.58572

2.4 Artificial Neural Network Overview
One way to mimic the brain's functionality on a computer is via an artificial neural network (ANN). Computers now process data sequentially rather than all at once, giving rise to a new kind of AI called artificial ANN. A neural network in a living organism was the basis for an artificial neural network. The ANN may represent complex non-linear problems. "Node connectivity is a complex, non-linear functional representation of the input-output connection, similar to neurons."

2.4.1 Node Character
The data is sent to every node. Once the activated signal has gone through the activation function, it is sent to the other nodes. "All functions and derivatives of sigmoidal functions are continuous. Equation (1) provides the Equation for the sigmoidal function."

$$Y= 1/(1+e^{-\beta x}) \quad (1)$$

Where y= dependent variable
X= independent variable
β= coefficient of independent variable

2.4.2 Network Structure
Linear layers arrange the network's nodes, including input, hidden, and output. Layer count, node density inside each layer, and route length between nodes define the node layout. Two types of connections—one-way and other—with a return loop are the most typical. The connections between nodes in a neural network allow it to be classified as either a feed-forward or feedback network.

2.4.3 Learning
As part of its learning process, ANNs undergo weight modification throughout training. Supervised and unsupervised learning are the two main categories of knowledge acquisition. "In supervised learning, a sequence of inputs and matching target outputs are provided." In unsupervised learning, the output is achieved only by using the input data from the training network. "The two most popular ANN learning algorithms are error correction and nearest neighbor. Error correction is an everyday use of the back-propagation method."

3. RESULTS AND DISCUSSIONS
In Table 2, you can see the values of the relevant influencing factors considered throughout the experiment. "For each trial, the level of combinations of the input design parameters is calculated using the Taguchi L27 orthogonal array for surface roughness." Experiment results led to the recommendation of using the ANN method to simulate CNC turning.

Artificial Neural Network Model Development for Surface Roughness
In order to forecast Surface Roughness values in connection to experiments, an ANN model was trained using the statistical software MATLAB (Version 8.1.0.604). "The present research used four input factors

at three different levels (Table 2), with Ra serving as the outcome variable; using the 27 experimental data, an ANN model was developed; table 4 shows the training parameters and the settings for the following network characteristics that were considered while building the ANN."

$\mathrm{MSE} = \frac{1}{Q}\sum_{K=1}^{Q}[t(k) - y(k)]^2$ (2)

Where MSE = Mean Square Error
t(k) = experimental target output
y(k) = ANN output value
Q = total data set

To measure the network's performance, we use Mean Square Error (MSE). To get the MSE, use the formula in Equation (2). "In this study, a total of 27 experimental sets were considered; 18 of these sets were used for training the network, and nine sets were selected to evaluate the performance of the trained network." We utilized the nine datasets kept aside for training method validation to test the trained network.

Table 4: Training parameters of ANN

Name and Type of Network	Function of Training	Function of Adaptive Learning	Function of Performance	Total No. of neurons	Transfer function
ANN,Feed forward back propagation	TRAINLM	LEARNGDM	MAP	10	TANSIG

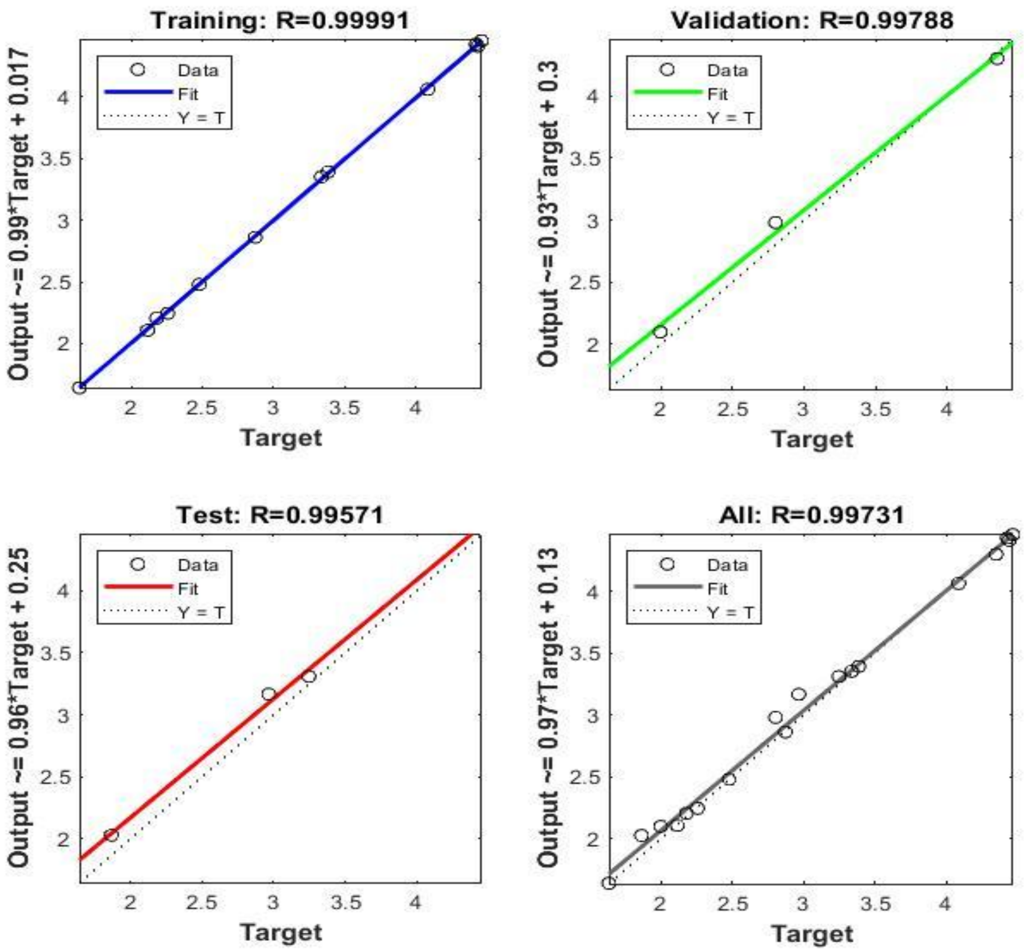

Fig 4: Regression plot

Figure 4 displays the regression graphs used by the ANN model for training, testing, and validating 18 sets of Ra experimental data. The graphs show the network's goals for the test set creation, analysis, and presentation. The goal values, the network outputs, were determined to be within 45 degrees of a straight line, and all sites were within that range. The 0.990 R-value shows an excellent match for all sets of data for Ra, which indicates a strong relationship between the experimental and predicted values. Table 5 displays the Ra values, both natural and trained by the ANN, for 18 sets of trials. Equation (3) was used to get the margin of error.

$$\text{Error} = \frac{1}{n}\sum_{1}^{n}\left[\frac{\text{experimental value} - \text{predicted value}}{\text{experimental value}}\right] \tag{3}$$

Table 5: Results for Ra taught via ANN compared to experimental methods

Sl no	Ra (exp)	Ra (ANN)	Ra % error
1	2.871	2.862	0.31
2	3.384	3.391	-0.21
3	4.084	4.061	0.56
4	2.802	2.979	-6.32
5	2.115	2.108	0.33
6	4.425	4.428	-0.07
7	1.864	2.245	-20.44
8	2.964	3.309	-11.64
9	4.464	4.298	3.72
10	1.636	2.026	-23.84
11	3.336	3.166	5.10
12	4.436	4.456	-0.45
13	1.831	1.640	10.43
14	3.331	3.352	-0.63
15	4.43	4.409	0.47
16	2.14	2.100	1.87
17	3.64	2.479	31.9
18	1.978	2.205	-11.48

To find the inaccuracy, we utilized Eq. 3. A little discrepancy existed between the experimental values and the trained ANN values—just a 2.64% average mistake.

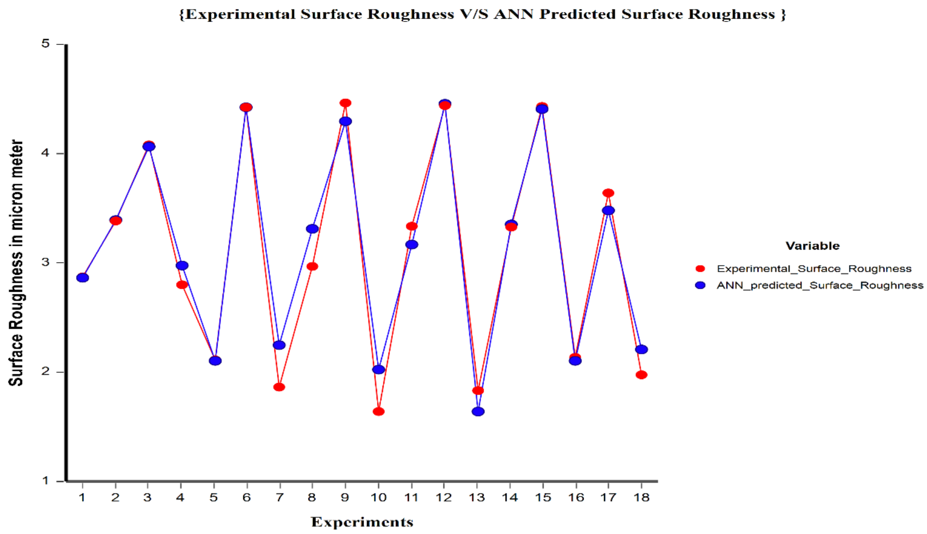

Fig 5: Experimental Ra vs. Trained ANN Ra Comparison Plot

Figure 5 shows the comparison charts of experimental values, ANN-trained values, and projected values for Ra. "The training and predicted value curves were found to be quite similar, and they were found to be

very similar to the actual experimental Ra values." The model's 1.70% deviation from experimental data makes it ideal for Ra prediction.
In order to validate the predicted values, the last sets of nine experiments—listed in Table 6—were considered. Very nothing changed between the experimental and tested sets of data. "The closeness of the predicted values of the testing ANN to the experimental values is seen in Figure 6."

Table 6: Compared Ra's ANN findings to experimental data

Sl no	Ra (exp)	Ra (ANN)	Ra % error
1	2.2561	2.3184	-2.76
2	3.2461	3.2787	-1
3	4.3461	4.3457	0.01
4	1.998	2.0681	-3.51
5	2.478	2.5337	-2.25
6	2.178	2.2427	-2.97
7	1.945	2.0167	-3.69
8	3.18672	3.2211	-1.08
9	4.58572	4.5781	0.17

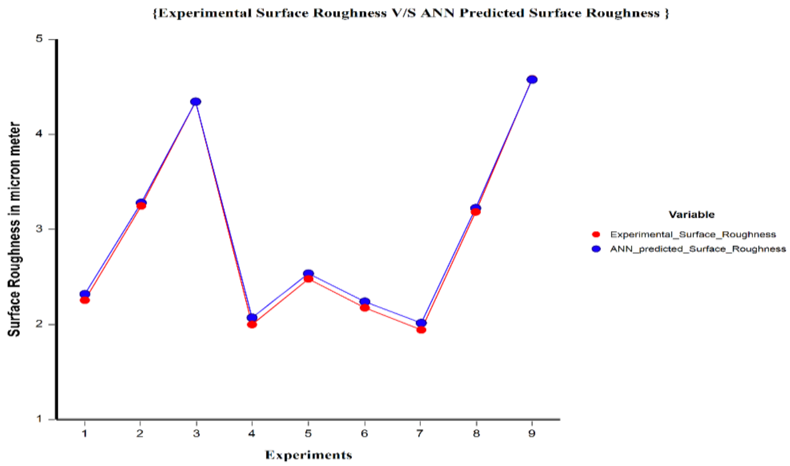

Fig 6: Examining the Relationship Between Experimental Ra and Predicted ANN Ra

Figure 7 shows a comparison plot of tested values for surface roughness with values predicted by artificial neural network (ANN) models. "The predictive capability of the ANN model is higher due to its ability to describe more complex nonlinearities and interactions among the parameters." Neural network modeling eliminates the need to pre-process the collected data pattern by automatically reducing noise during model training, resulting in excellent outcomes. Hence, ANN produces far more precise predictions of experimental outcomes. "In this experimental study, the ANN model outperforms the regression model in terms of resilience, marginal fluctuation error, and overall performance."

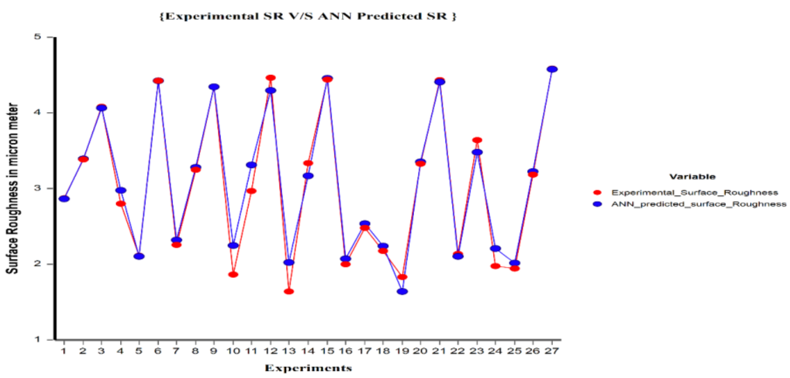

Fig 7: The correlation between Ra experimental measurements and the models' anticipated values

4. CONCLUSIONS

The primary objective of this study was to build an empirical model for CNC turning composites using an artificial neural network. "To forecast values for surface roughness, an ANN model was trained using MATLAB R2003a (8.1.0.604)". These findings are based on the experimental investigation.

1. An artificial neural network (ANN) was used to predict surface roughness using experimental data. The regression matrix can be used to estimate the Ra by calculating the regression coefficients using the regression matrix. Two values, R = 0.992 and R = 0.990 were found.
2. The neural network was trained using data from 18 of the 27 experimental sets, and its performance was evaluated using data from 9 of the experimental sets. There is a minor discrepancy of 1.89% in surface roughness.
3. The ANN models' predicted values were contrasted with the actual Ra experimental findings. When compared to the MSE model, the ANN model provides better predictions. Using the built and trained ANN model, one may more accurately predict the Ra by CNC turning using the provided set of machining parameters.

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