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Comparative study of surface roughness prediction using neural-network and quadratic-rotatable-central-composite-design

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ABSTRACT

The act of sustainable manufacturing lies in the response's prediction analysis, such as surface roughness during machining operations with nano-lubricant. This research focuses on developing a mathematical model to predict the experimental results of surface roughness of AA8112 alloys obtained during the end-milling process with an eco-friendly nano-lubricant. The study employed vegetable oil as the base cutting fluid (copra oil) and Titanium-dioxide (TiO2) nanoparticles as an additive. The end-milling machining was carried out with five machining parameters. The prediction analysis was done with a backpropagation feed-forward neural network (BPNN) and quadratic rotatable central composite design (QRCCD). The results show that the BPNN predicted the experimental results with 99.85%, and the QRCCD predicted 91.1%. The error percentage from both prediction analyses is 0.2% from the BPNN and 0.9% from the QRCCD. Therefore, the application of BPNN has proven viable in predicting surface roughness in machining operations. It will also improve the manufacturing industry's productivity and eliminate the high rate of waste materials during machining.

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1. INTRODUCTION

The manufacturing industry is the engine room for sustainable development for any nation [1]. The constant production of quality goods and services lies significantly with the production techniques involved in the industries [2]. One primary method in producing mechanical components is machining operations, mostly carried out with computer numerical control (CNC) machines [3]. Furthermore, the quality of the element developed is mainly accessed with the external surface finishing [4], [5]. The end-milling machining process is dynamic; however, unwanted vibration and friction between the cutting parameters and the workpieces have led to a rough surface [6], [7]. In order to eliminate this high surface roughness from developing machine parts, researchers have been investigating different techniques in machining operations such as nano-lubrication machining, cryogenic, nano-minimum quantity lubrication (NMQL). NMQL machining has successfully reduced the heat generated at the cutting region from existing literature, reducing vibration [8]–[11]. Therefore, to obtain a sustainable outcome of sound production output, there is a need to forecast the result obtained during the end-milling operation. The prediction analysis will help the manufacturing industry gain knowledge of the expected surface finishing of their product before carrying out the machining operation. Sharkawy [12] carried out a comparative prediction of the surface roughness of AL6061 alloys using three predictive tools, such as radial basis function neural networks (RBFNs), adaptive neuro-fuzzy inference systems (ANFISs), and genetically evolved fuzzy inference systems (G-FISs). The study employed three machining parameters: cutting speed, depth-of-cut, and feed rate in the end-milling machining process. The result obtained in the prediction analysis is that ANFISs could not predict the surface roughness due to the machining parameters selected for the operation. The G-FISs also as less performance in the prediction. However, the RBFNs could predict the surface roughness more accurately than ANFISs and G-FISs.

Lin *et al*. [13] employed the regression method and artificial neural network to predict the surface roughness. The authors used three machining parameters, i.e., cutting speed, depth-of-cut, and feed rate. The authors aim to validate which predictor can predict the surface roughness more accurately. However, the result shows that the artificial neuron network (ANN) predicts the experimental result of the surface roughness better than the regression method with 96%. The regression method has 82%. Therefore, the authors concluded that ANN is feasible in surface roughness prediction. Any raw materials cannot be done successfully without applying cutting parameters. These cutting parameters have significant effects on surface roughness. Okokpujie *et al*. [14] studied four parameters' impact on surface roughness. However, the study was able to identify the importance levels of the parameters during the machining of AL6061 alloys. Okokpujie *et al*. [15] conducted a comparative analysis of the least square approximation method and response surface methodology to predict the Al6061alloy's surface roughness result obtained during the end-milling machining operation. The authors concluded that the response surface methodology (RSM) predicted the surface roughness more accurately than the least square approximation method; both have the 99.6% and 99% prediction rates, respectively. Okokpujie *et al*. [16] worked on the experimental analysis of the SiO_2 nano-lubricant on the surface roughness of AL6063 alloys during turning operation. They predicted the experimental result using the box-Behnken design. The result shows that the box-Behnken has an accurate prediction result in the SiO_2 nano-lubricant environment. One significant thing in this study is that the nano-lubrication condition produces less surface roughness during machining operations.

A significant challenge in machining operation is managing the machining parameters during the production of engineering parts to have quality and good surface finishing [17]. Much research on the nano-lubricant's experimental performance during machining is limited in implementing the parameters without looking at its future performance [18]. Secondly, the helix angle is a significant machining parameter that needs experimental analysis and prediction to enable sustainable machining operation in AA8112 alloys. The application of backpropagation-feed-forward neural network (BPFNN) to predict the helix angle alongside other machining parameters has not been studied. Also, the prediction of surface roughness of aluminum alloys cannot be overlooked because it is the art of a sustainable manufacturing process. One of the significances of the study is that the prediction analysis is done on the nano-lubrication environment using TiO_2 nano-lubricant with vegetable oil, which assisted the machining operation of AA8112 alloys. By reducing the material adhesion during operations. This material adhesion is one of the problems been encountered by manufacturers during the machining of aluminum alloys.

Therefore, this study aims to predict surface roughness results obtained during the end-milling of AA8112 alloys under vegetable-based TiO_2 nano-lubrication. The study employed the quadratic rotatable central composite design (QRCCD) and backpropagation-feed-forward neural network (BPFNN) as the prediction tools. The most significant five-factor, five-level machining parameters, namely spindle speed, Length-of-cut, helix angle, depth-of-cut, and feed rate, have not been studied. There is a need to conduct prediction analysis by examining the helix angle with other machining parameters using QRCCD and BPFNN. This study will help the manufacturing industry develop machine parts and reduce production costs. In this study, the prediction accuracy of the QRCCD and BPFNN will also be compared to study their rate of prediction of the surface roughness of the AA8112 alloys.

2. RESEARCH METHOD

The end-processing activity utilized a five-factor five-level investigation, with nano-greases (TiO2-based copra oil) utilized as the cutting liquid. The CNC processing machine utilized for this work is at prototype engineering development institute (PEDI) in Ilesha, Osun State, Nigeria. The investigation was executed on the SIEG 3/10/0016 table-top CNC flat processing machine with three plane tomahawks: x, y, and z planes. With an end-milling capacity of 16 mm, spindle taper MT3, face milling 63 mm capacity, and power 1 kW. Also. Voltage 220-240 v, frequency 50 Hz, feeding speed max 500 mm/min, and rapid movement 2000 mm/min. The spindle travels 270 mm, the table travels 300×120 mm, spindle speeds 100-5000 rpm, and repetition-oriented precision of 0.01 mm. Figure 1 shows the experimental setup used for this study. Also, the necessary number of end-processing cutting devices was utilized in this exploration to guarantee that the flank wears most extreme is underneath the standard of hardware wear (VB.max.)=0.2 mm. Notwithstanding, the examination just considered space processing cutting mode.

The CNC part programs were developed for the machining operation, with specific commands. The different lengths of cut, feed rate, axial depth-of-cut, helix angles, and spindle speed were implemented concerning the Y-axis and Z-axis. This reference of the Y and Z-axis is done for all 50 samples. Figure 1 illustrates the experimental setup of the ending-milling of AA8112 alloys. Table 1 shows the machining parameters employed for the end-milling operations.

The copra oil-based TiO_2 nano-lubricant employed in this study is prepared using the two-step method. TiO_2 nanoparticles of 15 nm were dispensed into the copra oil using a mechanical, magnetic stirrer, and sonicator machine for proper homogenization. 0.6 g of TiO_2 nanoparticles and one liter of copra oil were employed to form the TiO_2 nano-lubricant used in this research. After the nano-lubricant was developed, the transmission electron microscope (TEM) and energy dispersive spectrometer (EDS) analysis gave the formulated lubricants' chemical composition, as shown in Table 2. The M42-high-speed-steel cutting tool of 13 mm diameter was employed in this study, with molybdenum of 9.5%, Cobalt 8.25%, Chromium 3.9%, Carbon 1.1%, Tungsten 1.6%, and Vanadium 1.2%.

Figure 1. The end-milling experimental setup with the nano-lubricant

Table 1. Machining conditions for the experiment under copra oil-based TiO2 nano-lubricant

Parameters	Unit	-2	-1	0	+1	+2
Spindle speed	Rpm	2000	2500	3000	3500	4000
Length-of-cut	mm	20	30	40	50	60
Feed rate	mm/min	100	150	200	250	300
Helix angle	°	0	15	30	45	60
Depth-of-cut	mm	1	1.5	2	2.5	3

Table 2. Chemical composition of the copra oil and the copra oil-based nano-lubricant

Elements	Carbon	Oxygen	Silicon	Calcium	Magnesium	Aluminum	Titanium
Copra oil Weight %	25.5	35.3	22.2	12.3	1.25	1.3	-
Copra oil-based TiO_2 nano-lubricant Weight %	15.4	30.4	30.2	6.7	1.25	4.24	10

2.1. Mathematical modelling using backpropagation-feed-forward neural network

Backpropagation-feed-forward neural network is a part of the artificial neural network (ANN) packaging. It is a data handling technique that reproduces the natural nervous system using workstations. BPNN comprises several basic units known as neurons that use a precise model with simple workstations that receive input variables and correct output. These neurons are a group of data for information processing using connected links. Every neuron has an associated load based on the input variables' strength to determine the output responses.

A layer is a group of neurons arranged in parallel without interacting. The workstation consists of three processes: the input layer, hidden layer, and output layer. Variables are presented to the workstation via the input layer and transferred to hidden layers. The work is done through weight connections; the hidden layers determine the output responses layer. After the experiment has been carried out, the values of the responses are recorded. The neuron has a bias $\emptyset$, which is added with the weighted sum W_n and input variables (U_n) to determine the total net input (T_n), as presented in (1) [19], [20].

$$T_n = \sum_{i=1}^{n} W_n * U_n) + \emptyset \quad (1)$$

The neuron for this back-propagation feed-forward neural network (BPNN) has five (5) inputs, with five (5) weights; this weight is randomized during the training period of the BPNN. The transformation process is carried out through the sigmoid nonlinear transfer function (Z), given in (2).

$$Z = U_1 * W_1 + U_2 * W_2 + \cdots + U_n * W_n + \emptyset * 1 \quad (2)$$

Where the total net input (T_n), is transposed as given in (3),

$$\hat{T} = Y_{out} = \text{sigmoid } (Z) \quad (3)$$

the sigmoid transfer function (Z_i) is given in (4) as,

$$\text{Sigmoid } (Z_i) = \frac{1}{1 + e^{-Z_i}} \quad (4)$$

$$Y_{out} = W_{ni} * Z_i \quad (5)$$

the output (Y_{out}) is determined by multiplying the activated transfer function with the weight W_{ni} The inner last layer of the hidden neuron and the output layer are shown in (5). The error is e_i, is obtained by subtracting the experimental values from the predicted values. The equation is given in (6), and the total error (SSE) is computed using (7).

$$e_i = SR._e - SR._p \quad (6)$$

$$SSE = \frac{1}{2} \sum_{I=1}^{n} e_1^2 \quad (7)$$

Depending on the problem to be solved, Backpropagation-feed-forward neural network has numerous techniques for training a neural system. In this work, the BPNN was adopted to build and train the system to predict output parameters. The structure of the BPNN employed for this study is presented in Figure 2. The inputs (U_n) correspond to feed rate, spindle speed, length-of-cut, helix angle, and depth-of-cut, the signal (Ø) is the interior threshold of a neuron, i.e., the bias, and $Z_{i,}$ is the nonlinear transfer function for the BPNN.

The neuron is trained with 70% input data, 15% of the input data for testing. The remaining 15% of input data is used for the validation process. The reason for this selection of hidden layers is to train the model accurately for an excellent prediction rate for the five machining factors. The five (5) cutting parameters at five levels gave 50 investigational runs for each environment carried out under the TiO_2 nano-lubricant. The research/prediction design is shown in Figure 3.

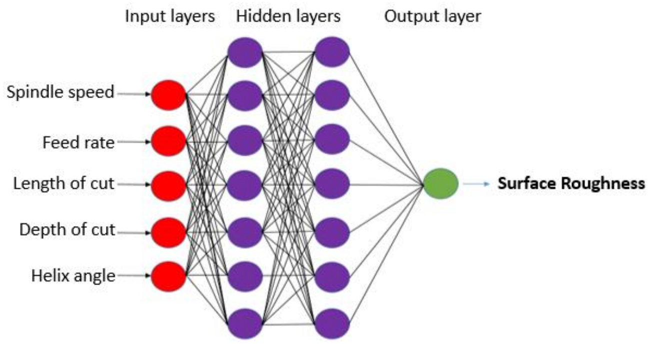


Figure 2. The neural network system structure for the surface roughness

2.2. Mathematical modelling using quadratic rotatable central composite design

Quadratic rotatable central composite design (QRCCD) is a design tool employed to analyze engineering problems. QRCCD is one of the packages in response surface methodology in Design expert software, mainly used for factors above four and five-level to study the relationship's effects on the response parameters. QRCCD is suitable for prediction, optimization, and model developments in the manufacturing of mechanical components. In this study, the relationship between surface roughness (the response parameters) and the cutting parameters under TiO_2 nano-lubrication cutting conditions is given in (8) [21], [22].

$$Y_i = \theta\,(S, F, L, D, \alpha) \tag{8}$$

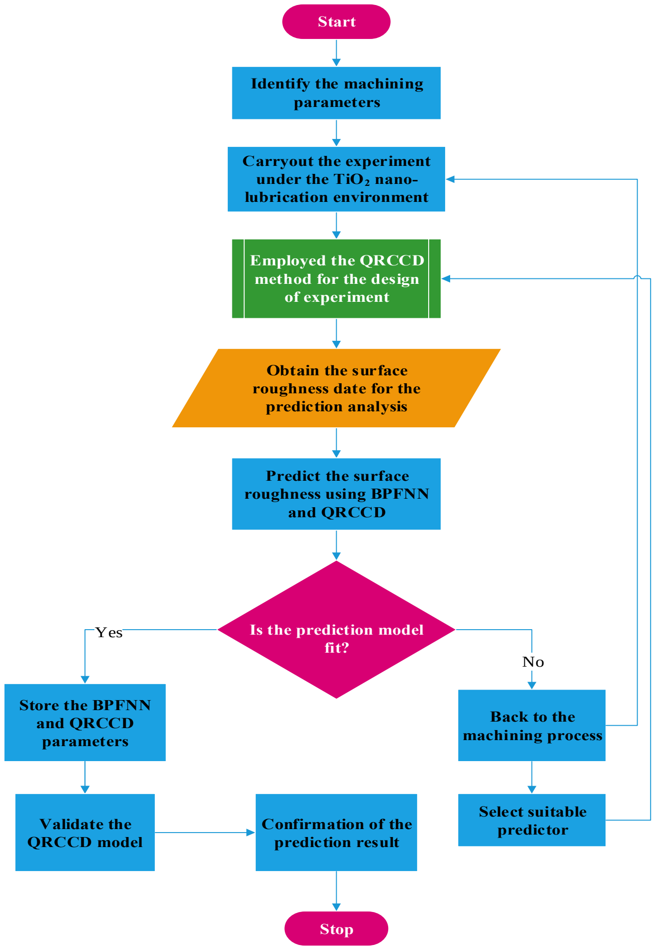


Figure 3. The flow chart showing the research design employed in this study

The desired machinability feature is Y_i and the response function is θ. However, the evaluation Y_i They are projected using a nonlinear scientific model, which is suitable for evaluating the effects of cutting parameters interface on machinability features. The interactions become (9).

$$Y_i = \theta\,(S^{X_x}, F^{Y_y}, L^{Z_z}, D^{zr}, \alpha^{zi}) \tag{9}$$

$$\log(Y_i) = \log(\theta) + X_x.\log(S) + Y_y.\log(F) + Z_z.\log(L) + Z_r.\log(D) + Z_i.\log(\alpha) \tag{10}$$

Where, $Y_i = \log(Y_i)$ $\beta_0 = \log(\theta)$ $x_1 = \log(S)$ $x_2 = \log(F)$ $x_3 = \log(L)$ $x_4 = \log(D)$ $x_5 = \log(\alpha)$ and $x = \beta_1, y = \beta_2, z = \beta_3, zr = \beta_4, zi = \beta_5$.

The overview of a replacement gets the following expression in (10), where the constant and exponents θ, X_x, Y_y, Z_z, Z_r, and Z_i are determined by the least-squares regression procedure. This research work, the Quadratic rotatable central composite design-based regression model second-order, is implemented and given in (11) as,

$$Y_i = \beta_0 + \sum \beta_i x_i + \sum \beta_{ii} x_i^2 + \sum \beta_{ij} x_i x_j + e(11) \tag{11}$$

the β_0 is the regression constant, $\beta_1, \beta_2, \beta_3, \beta_4,$ and β_5 are the coefficients, the logarithmic alteration of parameters are $x_1, x_2, x_3, x_4,$ and x_5. i.e., S, F, L, D, α, and e represent the spindle speed, feed rate, length-of-cut, depth-of-cut, helix angle, and the error term, respectively. The input variables and levels were undoubtedly within the interludes recommended by the computer numerical control manufacturer. In (11) is the regression model employed to develop the prediction model from the response surface method from the design experts.

3. RESULTS AND DISCUSSION

The data employed for the Backpropagation-feed-forward neural network (BPFNN) and the Quadratic rotatable central composite design (QRCCD) prediction of the surface roughness was obtained during the end-milling machining of AA8112 alloys under vegetable oil nano-lubricating conditions. This research's lubricating conditions are copra oil (as the base fluid) copra oil-based TiO_2 nano-lubricants for the machining process. Table 3 shows the surface roughness results with the coded factor values for the machining parameters under the TiO_2 nano-lubricant.

Table 3. Surface roughness results from copra oil-based TiO2 nano-lubricants machining

Run	Feed rate (mm/min)	Spindle speed (rpm)	Length-of-cut (mm)	Depth-of-cut (mm)	Helix angle (o)	TiO2 SR (µm)
1	-1	-1	-1	1	1	1.89
2	1	-1	1	1	-1	1.91
3	1	-1	-1	-1	-1	1.83
4	1	1	1	-1	1	1.43
5	1	-1	-1	-1	1	1.6
6	-1	-1	1	-1	1	1.53
7	0	0	0	0	0	1.5
8	1	1	-1	1	1	1.48
9	-1	-1	1	1	1	1.51
10	-1	1	-1	-1	-1	1.41
11	1	-1	1	1	1	1.54
12	0	0	0	0	0	1.51
13	-1	-1	-1	1	-1	1.56
14	-1	1	1	1	1	1.51
15	-1	1	-1	1	-1	1.5
16	1	-1	-1	1	-1	1.61
17	1	-1	1	-1	1	1.59
18	0	0	0	0	2	1.56
19	0	0	0	0	0	1.55
20	0	2	0	0	0	1.15
21	0	0	0	0	0	1.55
22	2	0	0	0	0	2.25
23	-1	1	1	-1	1	1.46
24	0	0	2	0	0	1.58
25	0	0	0	-2	0	1.53
26	-1	1	-1	-1	1	1.33
27	1	1	-1	-1	1	1.48
28	1	1	1	1	1	1.58
29	-1	1	-1	1	1	1.56
30	-1	-1	1	-1	-1	1.77
31	1	-1	1	-1	-1	1.85
32	0	0	0	0	0	1.51
33	1	1	1	1	-1	1.49
34	0	0	0	2	0	2.17
35	-1	1	1	-1	-1	1.51
36	0	0	0	0	0	1.58
37	-1	1	1	1	-1	1.49
38	-2	0	0	0	0	1.18
39	1	1	1	-1	-1	1.47
40	0	-2	0	0	0	2.15
41	0	0	-2	0	0	1.48
42	1	1	-1	1	-1	1.46
43	-1	-1	-1	-1	1	1.59
44	1	1	-1	-1	-1	1.45
45	0	0	0	0	-2	1.58
46	-1	-1	1	1	-1	1.61
47	1	-1	-1	1	1	1.62
48	0	0	0	0	0	1.58
49	0	0	0	0	0	1.58
50	-1	-1	-1	-1	-1	1.62

3.1. The QRCCD model and the prediction of surface roughness under TiO2 nano-lubricant

This section explains the development of the QRCCD model and the significance of the individual machining parameters involved in the end milling machining of AA8112 Alloys with TiO_2 nano-lubricant. From the QRCCD, the model developed was significant and with an F-value of 44.11. This indicates that the variation of vibration (error) happening is 0.01%. The significant parameters are obtained with the P-value. Any parameter with a P-value below 0.05 shows that the model's parameter is significant. The parameters greater than 0.1 are not important in the model. The vibrant parameters obtained under machining operation with TiO_2 nano-lubricant include S, F, D, S.D, S.α, F.α, L.α, D.α, S^2, F^2, D^2, S.F.L, S.F.α, S.L.α, F.L.D, F.D.α, L.D.α, S^2.F, S.F^2, D^3, S.LD.α, S^2.F^2 as present in Table 4. The F-value of lack-of-fit is 1.32; this designates that lack-of-fit is insignificant compared to the error value**.** From Table 5, a good precision value of 35.201 was measured during the analysis. This indicates that precision is adequate and that the signal-to-noise ratio has a noble correlation. The generated model can be used to direct the plan space. The prediction analysis used the stepwise method, which selected the significant parameters that could have a good prediction fit. This result of the excellent fit achieved by the stepwise QRCCD is in line with the observation given by Yang *et al*. [23].

The ANOVA coefficient estimation is a significant feature of the investigation regarding the predictable alteration in each machining factor's surface roughness per unit variation. The orthogonal design intercept for surface roughness average on the experimental runs. The ANOVA used the coefficients to adjust the cutting parameters' settings.

Table 4. The analysis of variance (ANOVA) result of QRCCD for the experimental results of surface roughness with TiO2 nano-lubricant

Source	Sum of Squares	Df	Mean Square	F-value	p-value	Remarks	
Model	2.09	34	0.0615	46.19	< 0.0001	99.05	Significant
S	0.5	1	0.5	375.23	< 0.0001	23.69	
F	0.5724	1	0.5724	429.61	< 0.0001	27.13	
L	0.0001	1	0.0001	0.0675	0.7985	0.005	
D	0.0194	1	0.0194	14.53	0.0017	0.919	
α	0.0002	1	0.0002	0.1501	0.7039	0.009	
S.F	0.005	1	0.005	3.75	0.0718	0.237	
S.L	0.0025	1	0.0025	1.84	0.1952	0.118	
S.D	0.0136	1	0.0136	10.22	0.006	0.645	
S.α	0.0276	1	0.0276	20.72	0.0004	1.308	
F.L	0.005	1	0.005	3.75	0.0718	0.237	
F.D	0.0055	1	0.0055	4.14	0.06	0.261	
F.α	0.0136	1	0.0136	10.22	0.006	0.645	
L.D	0.0036	1	0.0036	2.71	0.1204	0.171	
L.α	0.0351	1	0.0351	26.35	0.0001	1.664	
D.α	0.0288	1	0.0288	21.61	0.0003	1.365	
S^2	0.0167	1	0.0167	12.51	0.003	0.791	
F^2	0.0454	1	0.0454	34.05	< 0.0001	2.152	
L^2	0.0007	1	0.0007	0.5003	0.4902	0.033	
D^2	0.15	1	0.15	112.57	< 0.0001	7.109	
SF..L	0.0091	1	0.0091	6.84	0.0195	0.431	
S.F.α	0.0288	1	0.0288	21.61	0.0003	1.365	
S.L.D	0.0002	1	0.0002	0.1501	0.7039	0.009	
S.L.α	0.0338	1	0.0338	25.37	0.0001	1.602	
S.D.α	0.0028	1	0.0028	2.11	0.1669	0.133	
F.L.D	0.0364	1	0.0364	27.35	0.0001	1.725	

S= Spindle speed, F = Feed rate, L=Length-of-cut, D= Depth-of-cut, α=Helix angle

Table 5. Statistical analysis for QRCCD of the experimental result of surface roughness for TiO2 nano-lubricant

Standard Deviation	0.0365	R^2	0.9905
Mean	1.58	Adjusted R^2	0.9691
Coefficient of Variation (CV) %	2.30	Adequate Precision	36.0172

The purpose of the variance inflation factor's (VIFs) value is to determine the prognosticator model's presence and the variable parameter used to predict the surface roughness. A VIF value of one (1) means the element is orthogonal. The VIF value greater than one (1) implies multi-collinear parameters. The larger the VIF, the greater the multi-collinearity of the factors' interactions, and the experiment used the 95% confidence level (Cl). Furthermore, Table 4 shows the significance of the machining parameters on the surface roughness, which shows that feed rate and spindle speed has the highest contribution ratio in the surface roughness analysis. Figure 4 illustrates the effects of the individual parameters on the TiO_2 nano-lubricant surface roughness during the machining process.

The machining parameters are employed in the end-milling process to produce the product. The parameters considered in the study are the helix angle, spindle speed, feed rate, depth of cut, and length of cut. From Figure 4, it can be seen that the spindle speed has significant effects on the surface roughness, which illustrates that as the spindle speed increases, the surface roughness reduces. The five-in-one graph also explains the feed rate's effects by implying that as the feed rate increases, the surface roughness increases due to vibration occurrence n the machining region. The cut length is mainly influenced by the spindle speed, which makes its effects almost negligible. However, the depth of cut increases and increases the surface roughness. In the aspects of the helix angle, has the value increases, it increases the rate at which the chips is removed from the workpiece. Ann the increase assists in the fast production process; simultaneously, it reduces the surface roughness. The helix angles assist the free flow of lubricant to penetrate the machining region with an excellent cooling air system since the lubricant system is via a minimum quantity lubrication process.

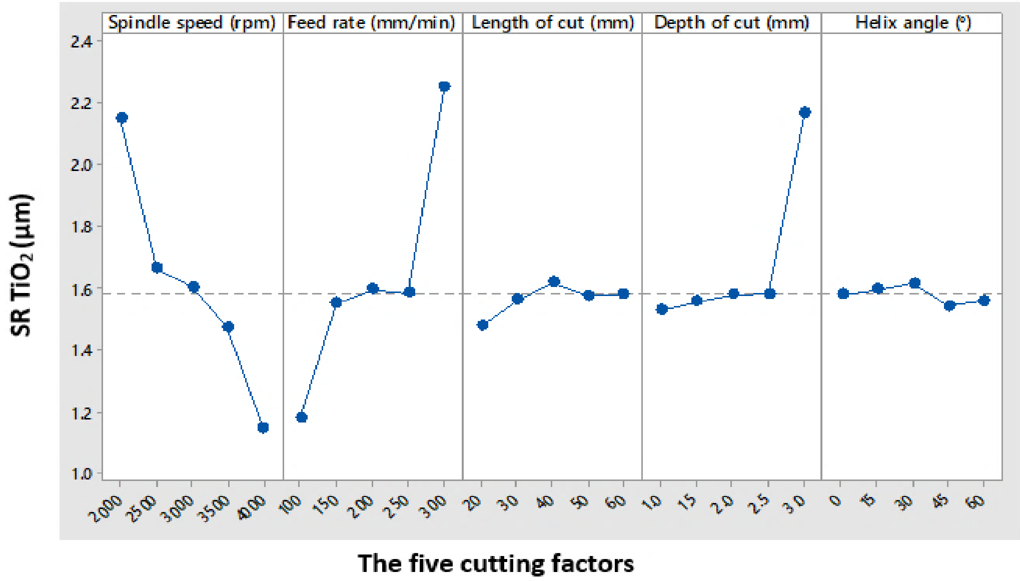


Figure 4. The effects of the five factors on the SR under the TiO2 nano-lubricant condition

The mathematical model developed to analyze the surface roughness under the TiO_2 nano-lubricant machining environment using the QRCCD is presented in two forms: (i) coded and (ii) actual. In (12) gives the model in the coded form. In (13), the model is coded to identify the machining factors' comparative effect or parameters when comparing the coefficients. The model is used to predict the surface roughness as shown in Figure 5.

$$\begin{aligned}
\mathrm{S.R.}_{coded} &= 1.55 - 0.5S + 0.54F + 0.01L - 0.07D - 0.01\alpha - 0.05SF + 0.03SL \\
&+0.08SD + 0.12S\alpha + 0.05FL - 0.05FD - 0.08F\alpha - 0.04LD - 0.13L\alpha + 0.12D\alpha \\
&+0.11S^2 + 0.17F^2 - 0.02L^2 + 0.31D^2 + 0.03\alpha^2 - 0.14SFL + 0.24SF\alpha + 0.02SFD \\
&+0.26SL\alpha - 0.07SD\alpha + 0.27FLD - 0.12FD\alpha - 0.13LD\alpha - 2.01S^2F - 0.17S^2\alpha \\
&+1.24SF^2 + 0.05L^3 + 0.39D^3 + 0.32SLD\alpha - 1.96S^2F^2
\end{aligned} \tag{12}$$

The model expressed in the fundamental factors is given in (13). The actual parameters model was employed to predict the response within specific levels of the controlled machining parameters.

$$\begin{aligned}
\mathrm{S.R.}_{actual} &= -41.12 + 0.02S + 0.65F - 0.02L + 1.84D - 0.13\alpha - 0.0004SF \\
&+0.00003SL + 0.0008SD + 0.00005S\alpha - 0.00004FL - 0.005FD - 0.0002F\alpha \\
&+0.022LD + 0.002L\alpha + 0.092D\alpha - 3.16E - 06S^2 - 0.002F^2 - 0.001L^2 \\
&-2.060D^2 - 6.75E - 08SFL + 8.00E - 08SF\alpha - 0.00002SLD - 6.33E \\
&-07SL\alpha - 0.00002SD\alpha + 0.00014FLD - 0.00004FD\alpha - 0.002LD\alpha + 5.44E
\end{aligned}$$

$$-08S^2F - 5.67E - 09S^2\alpha + 1.24E - 06S\,F^2 + 5.63E - 06L^3 + 0.393D^3$$
$$+5.33E - 07SLD\alpha - 1.86E - 10S^2F^2 \qquad (13)$$

3.2. The prediction of surface roughness using BPFNN under TiO2 nano-lubricant

This section presents the prediction of surface roughness of the end-milling of AA8112 Alloys with TiO_2 nano-lubricant using BPNN. The backpropagation feed-forward neural network (BPNN) was employed to predict the experimental outcome using Levenberg-Marquardt (trainlm) to train the neuron for better performance. The sigmoid nonlinear transfer function (Z) was applied, while the error performance was analyzed with total sum squared error (SSE). The statistical formulation was presented earlier in (1) to (7). Figure 6 and Figure 7 shows the neuron network model used for the TiO_2 machining environment.

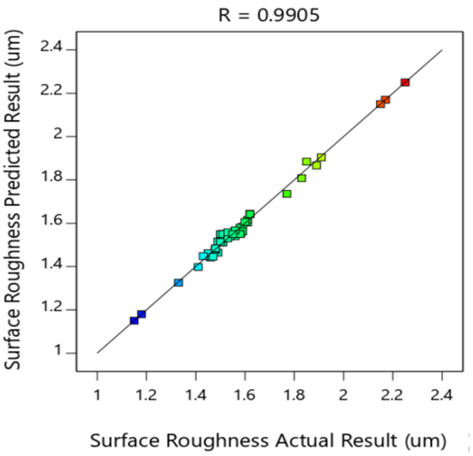


Figure 5. The experimental result vs. predicted result of the surface roughness under TiO2 nano-lubricant

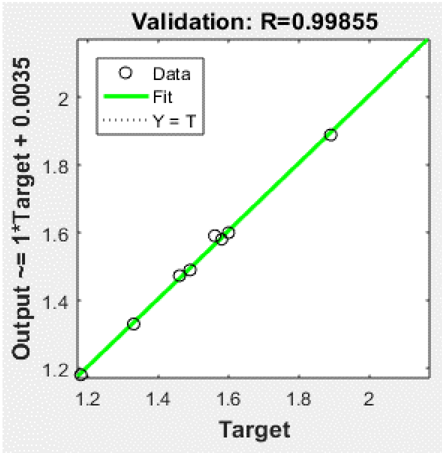


Figure 6. BPNN regression validation plot under the cutting environment of TiO2 nano-lubricant

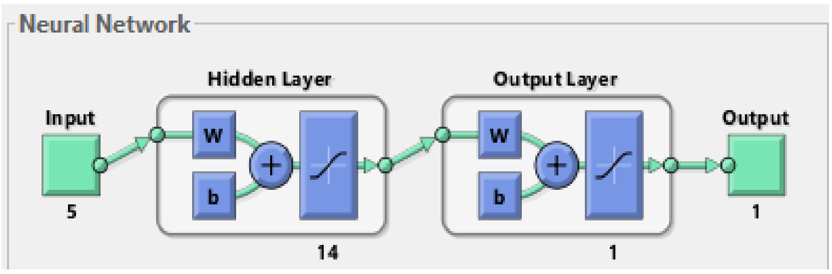


Figure 7. The BPFNN model used for the prediction analysis

Figure 6 to Figure 10 shows the performance analysis of the BPNN model with TiO_2 nano-lubricant using the sum of squared error (SSE) and coefficient relationship (R-value) of the regression model. The R-value explains the nearness of the predicted surface roughness using the BPNN model (i.e., output target) with the experimental result obtained through machining operation as shown in Figure 8. Also, Figure 9 and Figure 10 present the test analysis and all performance evaluation of the ANN prediction of the surface roughness under the TiO_2 nanolubricant.

From the analysis, the R-value for the data training set, data validation, and data testing is 0.91677, 0.99855, and 0.96291, respectively. This result is in line with the prediction analysis carried by [24]–[27]. This research's significant difference is the prediction of surface roughness of aluminum alloys using five-factor, five-levels, under vegetable oil-based TiO_2 nano-lubricant. Prediction analysis using the QRCCD and BPFNN to study helix angles and other cutting parameters has not been studied before now. Training, validation, and testing's overall performance is 0.93902, as depicted in Figure 9. Also, the solid line shows the regression model's performance level. The dashed line is also the regression model's perfect line. Both lines show the relationship between the target and the predicted surface roughness under the cutting environment of TiO_2 nano-lubricant. As measured by applying the SSE, the best validation performance from the BPNN model occurs at epoch 0 and iteration 6, as shown in Figure 11(a). The analysis shows that the mse decreased gradually from zero epoch to the peak point. Figure 11(b) shows the Marquardt unit parameter (Mu) gradient constant, total validation checks, and the iterations value. Prediction of the machine part's surface roughness is significant because it helps the manufacturer and the end-users achieve sustainable output during cutting operations. Also, surface roughness affects the fatigue life of the components [28].

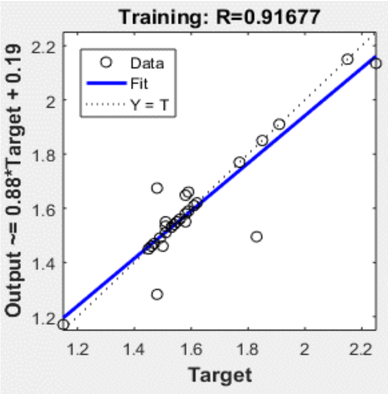


Figure 8. BPNN training analysis for the prediction of the surface roughness under the cutting environment of TiO2 nano-lubricant

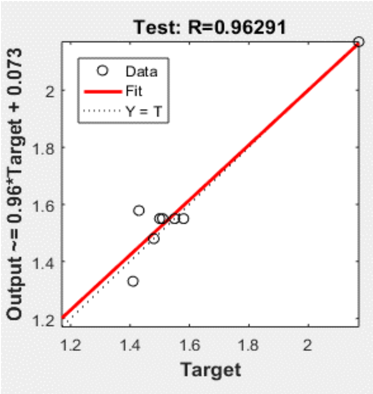


Figure 9. BPFNN testing regression analysis under the cutting environment of TiO2 nano-lubricant

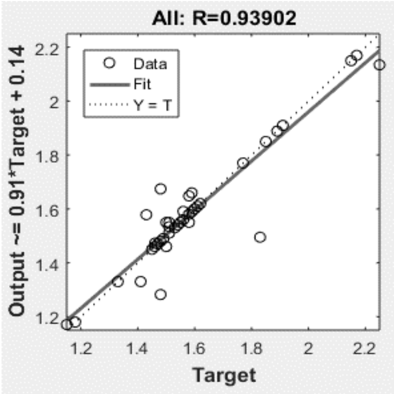
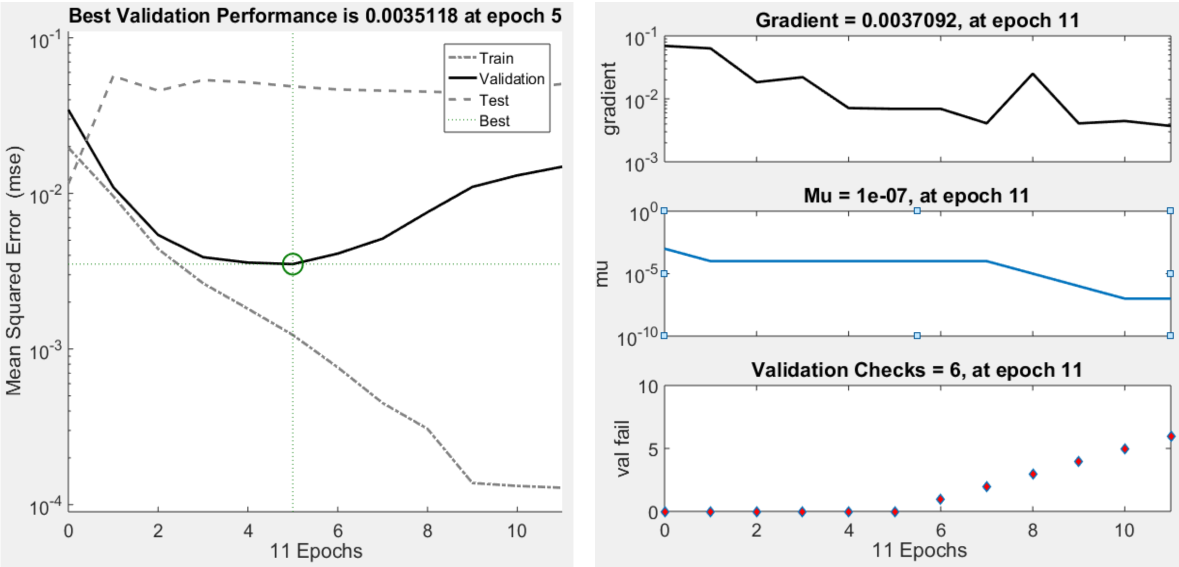


Figure 10. All performance plots of the BPFNN under the cutting environment of TiO2 nano-lubricant



(a) (b)

Figure 11. The ANN analysis of the surface roughness on the best performance and gradient, (a) BPFNN validation performance and (b) training state plot under the TiO2 nano-lubricant

3.3. The comparison of predicted results between BPNN and QRCCD for TiO2 nano-lubricant machining environment

The predicted models developed from the experimental data using BPFNN and QRCCD under machining operation of AA8112 alloys using TiO_2 nano-lubricant are depicted in Figure 12. From the comparative plot, it can be confirmed that the prediction of the BPNN is more accurate in predicting the experimental result obtained from the machining operation of the aluminum alloys. This study has proven that the ability of ANN to predict the end-milling surface roughness result for sustainable manufacturing of mechanical components for automobile and aerospace applications is viable. The data set from this study can be applied in the manufacturing industry to manufacture engineering parts with little or no surface roughness challenges, mostly when dimensional accuracy is highly needed. From literature, it has been proven that the power of predictions improves the production process and boasts the product's economic value [29]–[32].

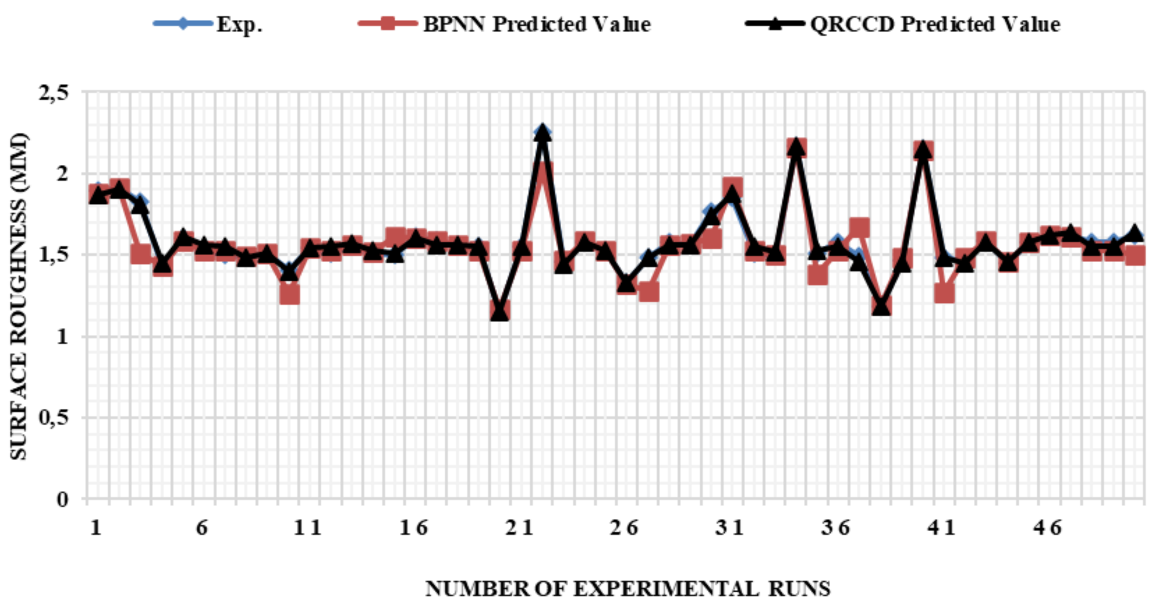


Figure 12. Experimental results, BPNN, and QRCCD predictions of the surface roughness under TiO2 nano-lubricant

4. CONCLUSION

Surface finishing for all machine parts is a significant parameter to justify the manufacturer's product quality. This study has successfully carried out five-factor, five-level end-milling machining experiments and studied the surface roughness under TiO_2 nano-lubrication. Also, to predict the experimental results to achieve a sustainable production process. Therefore, it is worth knowing that copra oil-based TiO_2 nano-lubricant is a sustainable cutting fluid that is eco-friendly the environment and with the end-users. Furthermore, the comparative analysis of the backpropagation-feed-forward neural network (BPNN) and quadratic rotatable central composite design (QRCCD) to predict the surface roughness of the AA 8112 alloys. For a sustainable production process. The study has the following conclusion drawn out: TiO_2 nano-lubricant machining environment is a sustainable cutting fluid for machining aluminum alloys with minimum surface roughness. This is one of the significant findings of this study that the BPNN prediction is carried out in an eco-friendly environment. Also, the study has proven that the spindle speed, length-of-cut, and helix angle relationship is very significant. The implementation of the helix angle also shows that helix angle, when increases in machining operations, reduces surface roughness. The backpropagation feed-forward neural network shows the validation result of 99.85% and the quadratic rotatable central composite design of 99.1%. Both predictors predicted the experimental result with high accuracy. Furthermore, the prediction rate was compared between BPNN and QRCCD, a difference of 0.75%. The science of prediction is a dynamic solution solved for future industrial activities. This prediction analysis gives manufacturers insight when producing mechanical components from aluminum alloys for aerospace and automobile application.

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