

Retraction

Retracted: Modelling and Analysis of Surface Roughness Using the Cascade Forward Neural Network (CFNN) in Turning of Inconel 625

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.



The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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Research Article

Modelling and Analysis of Surface Roughness Using the Cascade Forward Neural Network (CFNN) in Turning of Inconel 625

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In this paper, the influence of process components on surface roughness in turning of Inconel 625 using cubic boron nitride (CBN) is studied. A predictive model is developed to forecast the surface roughness using the cascade forward neural network (CFNN). The experiments are designed based on Taguchi. L_{27} orthogonal array (OA) is used to perform the experimental trails by considering speed, feed, and depth of cut as input factors. Out of 27 experimental trails, 18 experiments are used for training and 9 experimental trails are used for testing. The developed predictive model by the CFNN is compared with regression model values. The average prediction error for surface roughness is 2.94% with $R^2 = 99.99\%$ by the CFNN. The CFNN is known to be superior to predict the response with minimum of percentage error. The minimum and maximum roughness observed at trail 8 and trail 20 is noted, respectively, and the increases in roughness at experimental trail 8 is equal to 3.384 times higher than the roughness observed at experimental trail.20. The feed rate dominates effectively on the roughness rather than other factors. The consequences of process factors on surface roughness are studied with the help of ANOVA. This experimental study and developed model would be used for aero parts manufacturing to forecast the roughness accurately before to the actual experiment so that actual machining and material cost could be avoided.

1. Introduction

The roughness is an important and the quality of the surface roughness decides the integrity of the machined surface. Therefore, optimum of process factors is to be identified and also a predictive model is needed to be identified with minimum of percentage error. This work [1] stated that surface finish is the main index to know the idiosyncrasy of machined parts. They have developed the ANN model to forecast the mean roughness in machining the AA7075 alloy. The experiments were planned based on Taguchi. The feed-forward artificial neural networks (ANN) using the BR algorithm. Rahmath et al. [2] have used vibration signatures in turning steel alloy for the prediction of insert tool life using ANN techniques. They have developed as efficient indirect measurement of tool wear and it is found to be more economical and useful in predicting the tool wear. This paper [3] have proposed the ANN model to forecast

multiresponses in turning the aluminum alloy. The adequacy of the ANN structure was proved with $R^2 = 99\%$, mean squared error (MSE): less than 0.3%, and APE: less than 6%. They have considered the input factors such as cutting speed, feed, depth of cut (DOC), and radius of the nose with roughness, forces, temperature, material removal rate (MRR), power for cutting, and specific pressure for cutting as output.

Deshpande et al. [4] have performed turning operation on Inconel 718 and the surface roughness was foreseen using the developed ANN model. The ANN model-predicted results were compared with the regression model. They have concluded that the ANN framework was known to be the best to foresee the roughness with great accuracy than the regression model. These works by Boukezzi et al. [5, 6] said that ANN techniques emerge as the main tool to model the nonlinear problems in machining processes. They have reviewed the studies done on the application of the ANN.

They have concluded that the ANN showed great accuracy than other old statistical techniques and also, they have said that, researchers concentrated on more on wear and surface roughness owing to the prime role took part by surface integrity of the machine surface. Lakhdar et al. [7] have said that the development of the relationship among different machining conditions and machining performances are found to be the major objective of the industry. They have succeeded a predictive model in turning of steel to predict surface roughness using the ANN and RSM. The potential of both the model were evaluated using coefficient of correlation (R^2). The final results showed that the ANN model has performed better than the RSM.

The authors Sada et al. [8] have appraised the execution of the ANN and adaptive neuro-fuzzy inference system (ANFIS) in the prognosis of the metal removal rate and tool wear in machining of steel. They have concluded that, both the techniques have performed well; however, the ANN has produced best results rather than the ANFIS. These works by Paturi et al. [9] have evolved the model to predict surface roughness using machine learning techniques such as ANN, support-vector machines (SVM), and genetic algorithm (GA) in wire electro discharge machining (WEDM) of Inconel 718. The forecasted values by the ANN and SVM were compared with the response surface method (RSM) model based on correlation coefficient. The SVM model was found to be accurate rather than other methods. Moreover, the SVM and GA techniques have produced accurate prediction and optimization of the parameters. Machine learning technologies are recently used widely to predict the attributes before the actual experiment as well as these techniques are widely used for the measurements of the outputs [10]. It is also to be investigated for the best solution for optimum of outputs to reduce the wastage of material and cost of machining in machining [11–14].

Elsheikh et al. [15] said that, Inconel 718 is difficult to machine, and it possesses poor machinability and minimum conductivity. They have revealed that, machining of this alloy becomes critical and needs to be carefully monitored/controlled. Therefore, they have developed a hybrid machine learning (ML) tools to forecast the existence of residual stresses in turning of Inconel 718. The hybrid ML tool was named as the pigeon optimization algorithm (POA) and particle swarm optimization (PSO). The forecasted stresses were verified with the measured value. Yigit et al. [16] have investigated and developed a predictive model to forecast microhardness and grain size during machining of titanium alloy using finite element analysis and machine learning approach. They have reported the impact of the factors on roughness based on the prediction of microhardness and grain size. Further, they have optimized the machining factors based on the genetic algorithm. This work by Bhandari [17] has developed the deep learning (DL) structure to predict the roughness by considering multi-layer Perceptron (MLP), convolution neural network (CNN), long short-term memory (LSTM), and transformer to classify surface roughness using sound and force data. This investigation has highlighted that DL with the transformer model as superior than other DL models.

From the literature, it is evident clearly that, the machine learning (ML) techniques are mostly used to predict the machining responses with better regression coefficient and the %age error is also noted to be minimum among experimental and machine learning model's prediction. Furthermore, the predictive model development based on different machine learning techniques and regression model are all discussed, and limited reports was seen for the prediction of outputs in machining Inconel 625. Hence, this work is done to make a machine learning methodology to forecast the roughness, and the forecasted results are differentiated with experimental values and predicted values by the regression model. The impact of the input factors on the surface roughness is discussed using ANOVA.

2. Materials and Experimental Details

Inconel 625 grade 60 mm in diameter with the length of 150 mm were used to conduct experiments. The chemical portion of the work material is shown in Table 1.

Three levels and three factors such as speed, feed, and depth of cut were used for the experiment. A Taguchi design was adopted to conduct experimental trails as well as to choose the levels of the factors. The level ranges of the factors are given in Table 2. A design expert was used to carry out regression analysis. The experimental result of the surface roughness is specified in Table 3. A dry turning environment was chosen. The turning experimental trails are done using central lathe, and cubic boron nitride tools are utilized. Taguchi is used to plan the experiment and L_{27} array is used to do experimental trails [11–14]. The surface roughness was determined using surf-coder profilometer and an average of three measurements was taken at every machining condition.

3. Regression Analysis

The input factors and machining responses are modelled using quadratic regression equation as follows:

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_i \sum_j \beta_{ij} x_i x_j + \varepsilon, \quad (1)$$

where

'Y': machining attribute

x_i : is the value of the i^{th} factors

β : coefficient: regression

ε : residual measure

The values of experiment trails are predicted using the regression equation. The quadratic equation to predict the roughness is given in (2).

$$R_a = 1.70 - 0.01263 * \text{cutting speed} + 20.80599 * \text{feed} - 0.970968 * \text{DOC} + 0.120647 * \text{cutting speed} * \text{feed} - 0.000380 * \text{cutting speed} * \text{DOC} + 1.76252 * \text{feed} * \text{DOC} - 0.000033 * \text{cutting speed}^3.$$

$$138.666 * \text{feed}^2 + 0.273016 * \text{DOC}. \quad (2)$$

R-square value is 94.71% and the ability to predict the surface roughness is identified to be adequate. The developed

TABLE 1: Composition of Inconel 625.

S. no.	Compositions	Weight (%)
1	52.49:Ni	52.49:Ni
2	0.19:Si	0.19:Si
3	0.46:Mn	0.46:Mn
4	20:Cr	20:Cr
5	6.29:Mo	6.29:Mo
6	0.07:Cu	0.07:Cu
7	1.0:Fe	1.0:Fe
8	16.7:Co	16.7:Co
9	1.94:Ti	1.94:Ti
10	0.48:Al	0.48:Al
11	0.04:Nb	0.04:Nb
12	0.15:W	0.15:W
13	0.02:V	0.02:V
14	0.02:C	0.02:C
15	0.001:S	0.001:S
16	0.007:Ta	0.007:Ta

TABLE 2: Machining factors.

Factors	Cubic boron nitride		
	L 1	L 2	L 3
V : m/min	70	100	130
S : mm/rev	0.045	0.076	0.138
a_p : mm	0.15	0.3	0.65

TABLE 3: Experimental trail results.

Expt. trail no.	Speed	Feed	DOC	(Ra) μm
1	70	0.045	0.15	1.75
2	70	0.045	0.30	1.45
3	70	0.045	0.65	1.20
4	70	0.076	0.15	1.86
5	70	0.076	0.30	1.90
6	70	0.076	0.65	1.66
7	70	0.139	0.15	1.75
8	70	0.139	0.30	2.2
9	70	0.139	0.65	1.63
10	100	0.045	0.15	1.21
11	100	0.045	0.30	1.00
12	100	0.045	0.65	0.95
13	100	0.076	0.15	1.75
14	100	0.076	0.30	1.59
15	100	0.076	0.65	1.44
16	100	0.139	0.15	2
17	100	0.139	0.30	1.8
18	100	0.139	0.65	1.66
19	130	0.045	0.15	0.76
20	130	0.045	0.30	0.68
21	130	0.045	0.65	0.41
22	130	0.076	0.15	1.53
23	130	0.076	0.30	1.25
24	130	0.076	0.65	1.1
25	130	0.139	0.15	1.90
26	130	0.139	0.30	1.65
27	130	0.139	0.65	1.59

model is said to be 95% confidence interval. Figure 1 shows normal plot of residuals and the congregate of points that connect the normal plot for the residuals of the surface roughness. These points are very near to the plot and it is allowable with 95% confidence interval. The average %age error among experiment values and predicted result by the regression model is identified to be 2.311%.

4. Cascade Forward Neural Network (CFNN)

4.1. CFNN Model Implementation for Prediction of Surface Roughness. A popular approach for modelling and improving manufacturing processes is the artificial neural network (ANN) approach. In the manufacturing industry, choosing the best processing parameters is crucial in terms of both time as well as quality. This study examines how machining variables including feed rate, depth of cut, and spindle speed affect the surface roughness using cascade forward neural network models for Inconel alloy [11–14]. The neural network is created using the back propagation in such a way that, for all training input patterns, the sum squared error (Err) between actual outputs (Y) and its associated desired outputs (Y_d) is minimised to a predetermined value, as indicated by the following equation. The transfer function types for each tier must be chosen by trial and error in order to obtain the best network model.

$$\text{Err} = Y_d - Y. \quad (3)$$

Similar to feed-forward neural networks, cascade forward neural networks have connections from the inputs as well as every previous layer to subsequent levels. As shown in Figure 2, the output layer in a three-layer network is also directly connected to the input layer in addition to the hidden layer. A two or more cascade network layers may learn any finite input to turn relationship indefinitely well, provided there are more than enough hidden neurons, much like feed-forward networks do. All types of input to output mappings can be done with a cascade forward neural network. The benefit of this approach is that it preserves the linear link among input and output while accommodating the nonlinear relationship.

An ANN is a collection of interconnected, basic building blocks known as neurons. Particularly when there are many inputs and only one output, each neuron represents a mapping. The neuron's output depends on the total of its inputs. A neuron's output uses a function known as an activation function. The symbol for a single neuron displays the degree of arrows originating from the neuron because its single output can be used as an input by some other neurons. Through an activation function in the hidden layer, the relationship has a nonlinear shape. In addition to the connection that is generated indirectly, a network with a direct link between the input layer and the output layer is created when a multilayer network and perception connection are coupled. The cascade forward neural network (CFNN) is the name of the neural network created using this connection arrangement. Tables 4 and 5 show the dataset used for training and testing purpose.

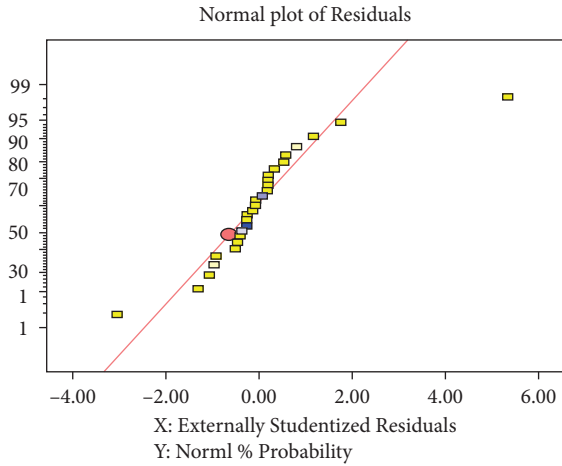


FIGURE 1: Normal plot of residuals of flank wear.

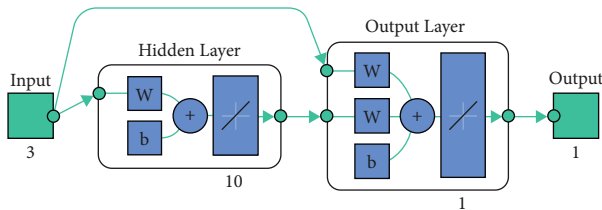


FIGURE 2: Two layered cascade forward back propagation network.

The feed forward of the input pattern, error counting, and adjustment of weight are the three stages of the back propagation method on the CFNN, as similar with feed forward neural network (FFNN). The method then moves on to the error calculation stage following the feed forward stage (the difference from the output to the target). The weights need to be updated, and a new calculation needs to be made. This step is repeated until no errors are found or the iteration reaches the predetermined stop criteria, whichever comes first. In this part, we provide a brief overview of the conjugate gradient optimization approach for the CFNN model weighting adjustments as illustrated in Figure 3.

The percentage error formula was used to obtain the average error prediction between the predicted out-turn and the target out-turn, as shown in (4) which is shown in Table 6.

$$\text{Percentage Error} = |C - P|/|C| \times 100. \quad (4)$$

C-measured value

P-predicted value

From Table 6, it can be deduced that the average surface roughness (R_a) prediction error is 2.94%. The neuron in the input layer be tuned with DOC, feed rate, and speed. The output layer, on the other hand, is correlated with surface roughness (R_a). According to the accuracy plot, the regression equation for the created CFNN model is depicted as $y = 0.9882x - 0.0217$ and has an R-squared value of 0.9864 as shown in Figure 4.

Eventually, the purelin function transfer produced the foremost results for neurons in hidden layers. Using the plot

TABLE 4: The training dataset with target output.

Expt. No.	V (m/min)	S (mm/rev)	a_p (mm)	Ra (μm)
2	70	0.045	0.3	1.45
3	70	0.045	0.65	1.2
4	70	0.076	0.15	1.86
6	70	0.076	0.65	1.66
7	70	0.139	0.15	1.75
8	70	0.139	0.3	2.2
10	100	0.045	0.15	1.21
12	100	0.045	0.65	0.95
13	100	0.076	0.15	1.75
14	100	0.076	0.3	1.59
17	100	0.139	0.3	1.8
18	100	0.139	0.65	1.66
19	130	0.045	0.15	2
21	130	0.045	0.65	1.55
23	130	0.076	0.3	1.65
24	130	0.076	0.65	2.5
25	130	0.139	0.15	2.3
26	130	0.139	0.3	2.25

TABLE 5: The test dataset.

Expt. No.	V (m/min)	S (mm/rev)	a_p (mm)
1	70	0.045	0.15
5	70	0.076	0.3
9	70	0.139	0.65
11	100	0.045	0.3
15	100	0.076	0.65
16	100	0.139	0.15
20	130	0.045	0.3
22	130	0.076	0.15
27	130	0.139	0.65

network execution function graph indicates that it was simple to empirically calculate the expected number of training epochs. On examining at the network training graph, it was noticed that after two epochs, the training network essentially stops as shown in Figure 5. Algorithms for learning modified the created neural networks to fit the data file during training. R is used to measure correlations between the target and anticipated values. MATLAB regression graphs as shown in Figure 6 displayed the outputs of the network in relation to the goals for the testing, validation, and training sets, with R^2 results above 0.99 for all datasets, were used to evaluate the accuracy of the fits.

5. Results and Discussion

The turning trails are carried out on Inconel 625, and the portending model is made by CFNN techniques and regression models. The effects of input factors on surface roughness are analyzed. The analyses of variance (ANOVA) is useful to find out the effect of every factor. The statistical importance of every factor is recommended using the P value. If the P value of a particular factor is noted as lower than 0.05, then that factor is statically significant on output. The ANOVA is obtained with significance of 5%.

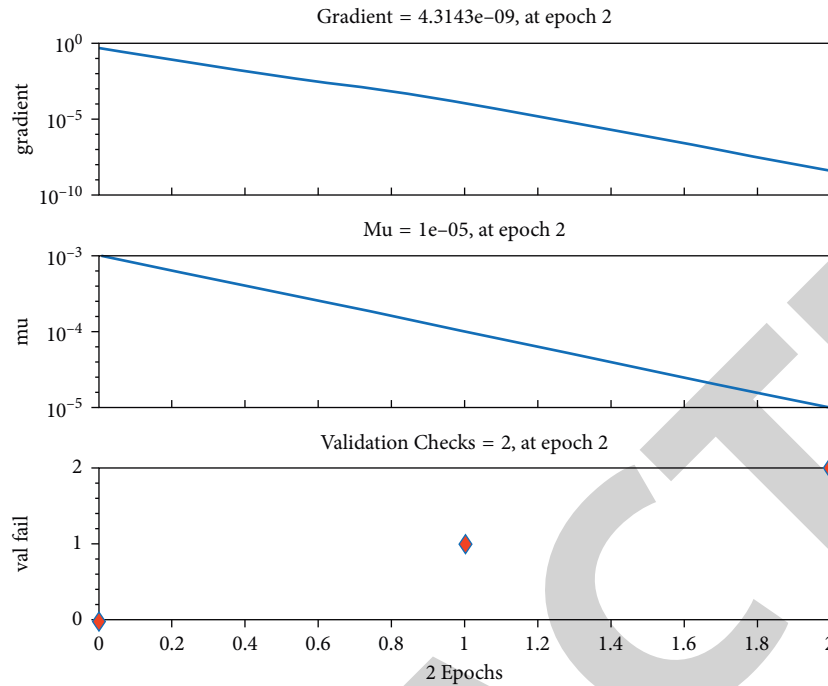


FIGURE 3: Performance plot of the CFNN model.

TABLE 6: Percentage prediction error.

Expt. No.	Surface roughnesses		% Prediction error
	Measured values	Predicted values	
1	1.75	1.640316	0.553368
5	1.9	1.856271	2.30152
9	1.63	1.561874	0.233902
11	1	1.123179	1.231789
15	1.44	1.306065	9.301023
16	2	1.97721	1.139501
20	0.68	0.758432	3.17173
22	1.53	1.421401	7.097955
27	1.59	1.427203	1.433798
		Average prediction error	2.94

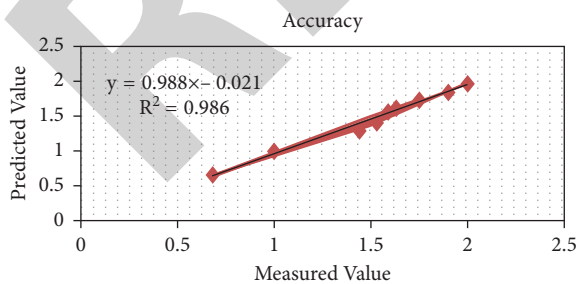


FIGURE 4: Accuracy plot of the CFNN model.

Furthermore, the significance of the factors on roughness can be seen according to F-value. In this ANOVA Table 7, feed rate (F-value: 164.88) and speed (F-value: 61.06) are all identified as significant on roughness followed by depth of

Best validation performance is 0.078773 at epoch 0

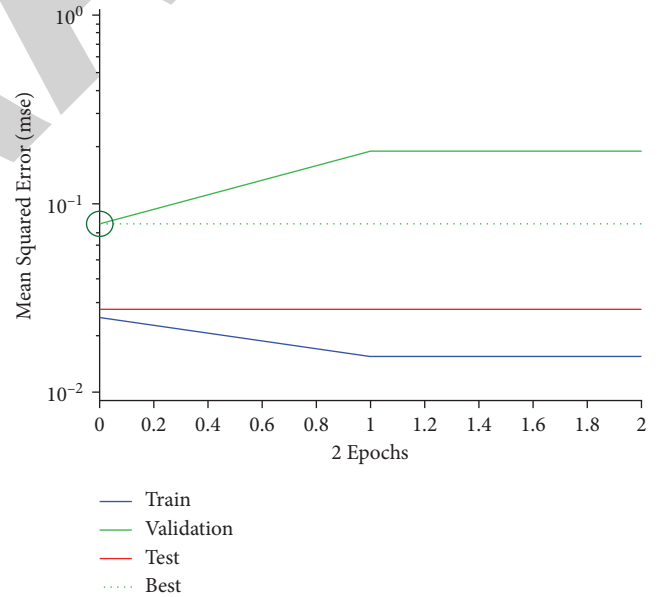


FIGURE 5: Plot of the training network.

cut (F-alue: 28.53). ANOVA analysis was carried out at a significant level of 5% with confidence level of 95%.

Figures 7(a)–7(c) illustrate the discrepancy in the surface roughness with respect to change in the level of process factors using three dimensional plots. The escalate in the feed rate causes the escalate in the roughness; however, the roughness is lowered as the level of cutting speed increase. There is no remarkable change in the roughness as the level of DOC changes. The scanning electron microscope (SEM) images evidently exhibited in Figures 8(a) and 8(b) that a

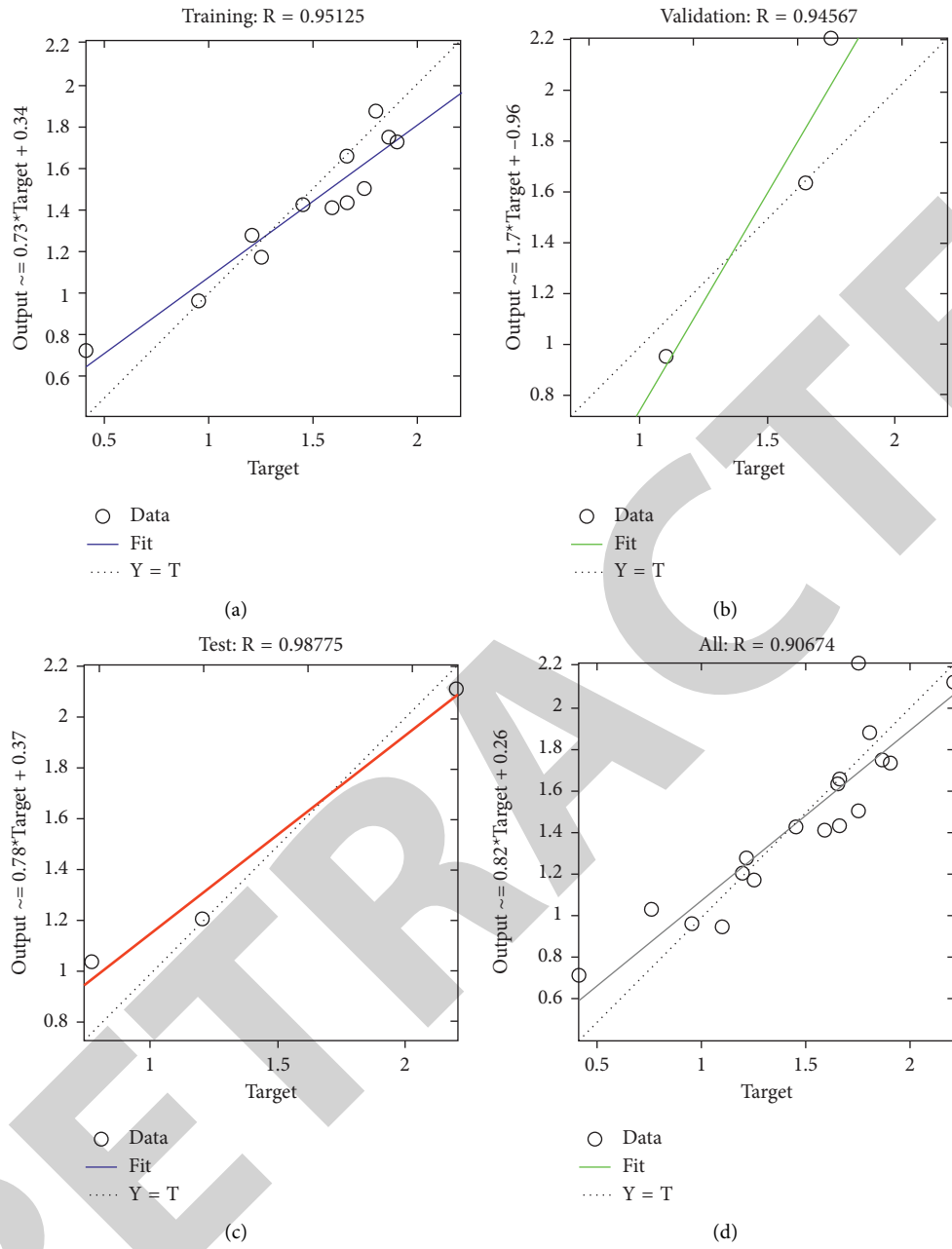


FIGURE 6: Plots of trained network with respect to target for (a) train, (b) validate, (c) test, and (d) all.

TABLE 7: ANOVA.

S	SOS	DF	MS	F	p
M	4.65	9	0.5169	33.79	<0.0001
V	0.9340	1	0.9340	61.06	<0.0001
S	2.52	1	2.52	164.88	<0.0001
a _p	0.4365	1	0.4365	28.53	<0.0001
V * S	0.3607	1	0.3607	23.58	0.0001
V * a _p	0.0001	1	0.0001	0.0067	0.9357
S * a _p	0.0056	1	0.0056	0.3681	0.5521
V ²	0.0052	1	0.0052	0.3400	0.5675
S ²	0.4237	1	0.4237	27.70	<0.0001
a _p ²	0.0012	1	0.0012	0.0765	0.7854
Residual	0.2601	17			
Total	4.91	26			

R²: 94.71%

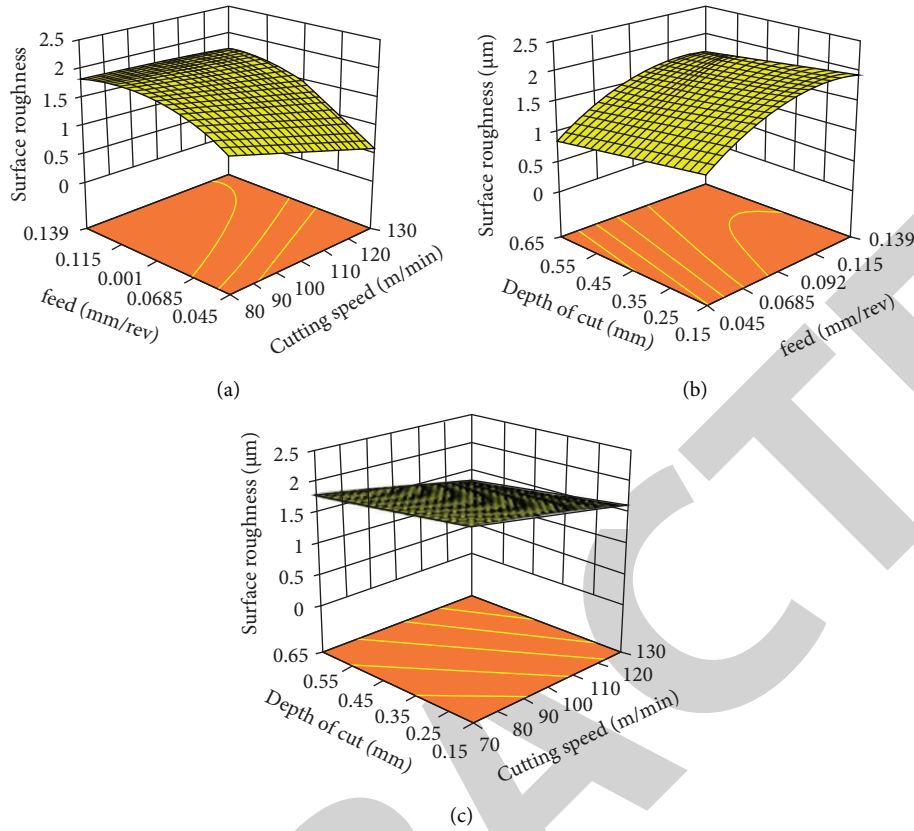


FIGURE 7: (a) Cutting speed Vs. feed, (b) feed Vs. depth of cut, and (c) cutting speed Vs. depth of cut.

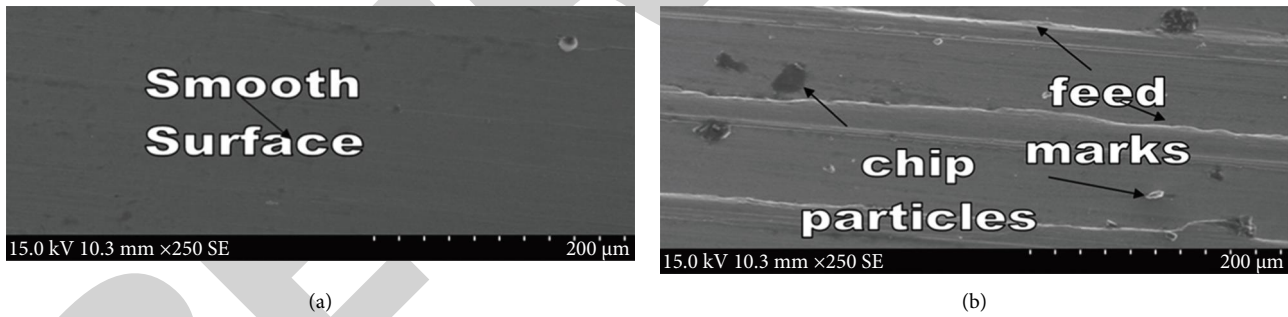


FIGURE 8: (a) At cutting speed = 130 (m/min), feed = 0.045 (mm/rev) and depth of cut = 0.30(mm), (b) at cutting speed = 70(m/min), feed = 0.139 (mm/rev) and depth of cut = 0.30(mm).

smooth surface is noted at higher cutting speed; whereas the rough surface is noted as the feed rate increases. The reason behind that at high level of speed, temperature generation in the cutting zone is more and it aids easy removal of the material. At higher feed rate, the coefficient of friction is more at cutting zone, hence rubbing takes place and as results rough surface is generated.

From the figures, it is revealed that the roughness is increased as the feed rate escalates and the corresponding insert flank wear, cutting force, and tool life are all noted only for the experimental trails 8 and 20. The noted results at experimental trails 8 and 20 are given in Table 8. It is a clear evidence from the tables the observed roughness, force, flank wears, and tool life. The insert tool life is calculated by

TABLE 8: Machining responses at Trail 8 and 20.

Trail. no.	Roughness (μm)	Force (N)	Flank wear (mm)	Tool life (sec)
8	2.2	475	0.39	225
20	0.65	290	0.32	450

measuring the insert flank wear at every 50 seconds once and the time period is noted at final insert worn out stage. The feed rate impacts mainly on these responses compare to other factors and it is accepted that, as the feed rate escalates the roughness, wear increases and life of the insert reduces [18, 19]. It is observed that the increases in roughness at trail 8 is equal to 3.384 times higher than the roughness observed

at trail 20. Similarly, force and flank wear observed at trail 8 is equal to 1.63 and 1.21 times higher than the trail 20, respectively. Furthermore, it is seen from the table that the tool life is found to be decreased as the level of feed rate increases at trail 8, whereas the life of the insert is increased as the level of feed rate is reduced. The insert life is significantly affected as the level of changing the feed rather than other factors in turning Inconel 625 using CBN insert.

6. Conclusions

From the analysis of the surface roughness during the turning of the Inconel 625 using CBN insert, the below conclusions were drawn:

- (i) The feed rate was found to influence the roughness more effectively than the speed and depth of cut, thus showing the importance of feed control in turning Inconel 625 using CBN insert.
- (ii) From seeing the SEM images, machined surface shows the feed marks, chip particle adhered including rough surface in turning Inconel 625 using CBN insert at a higher level of feed and lower level of speed.
- (iii) The predictive models developed by the regression and CFNN model were established to be fit well with experimental trail values. These predictive models can be useful to predict the surface roughness before actual experiments in the manufacturing factories.
- (iv) Inconel 625 dataset includes 27 trials, 18 for training, 9 for testing, and 4. The prediction potential of the ANN-CFNN model was proved as more perfect for the prediction of roughness than the regression model.
- (v) The average percentage error among experiment trails and CFNN model is found to be 2.94%.
- (vi) Based on the regression model developed from the experimental results for roughness, closeness is seen and 95% confidence level.

The developed predictive models for roughness would be very much useful in the difficult machine materials Inconel 625 for the aero part manufacturers. However, the influence of the factors on force, tool wear, and life of the insert in turning Inconel 625 using CBN insert to be analyzed as well as suitable novel machine learning tool to forecast the responses are to be found out.

Data Availability

The data used to support the findings of this study are included within the article. Further data or information are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

Acknowledgments

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