Research Article

Application of ANN to estimate surface roughness using cutting parameters, force, sound and vibration in turning of Inconel 718

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Abstract
In this paper, artificial neural network approach is used to predict surface roughness using cutting parameters, force, sound and vibration in turning of Inconel 718. Experiments were performed by using cryogenically treated and untreated inserts, and various responses were measured. Then, these measured responses were used as input to the artificial neural network to predict surface roughness. It is found that the models developed by artificial neural network are predicting surface roughness with more than 98% accuracy. Further, the predictions obtained by artificial neural network are compared with the results of regression-based prediction models earlier proposed by the authors. The modified regression models were estimating surface roughness with more than 90% accuracy. Based on correlation coefficient values, the prediction results of modified regression model are compared with those obtained by artificial neural network. Finally, it is concluded that artificial neural network models are better for estimating surface roughness than the regression models and such predictions are useful for real-time control of the process to acquire the desired surface roughness.

Keywords Artificial neural network · Surface roughness · Inconel 718

Abbreviations

CNC	Computer numerical control
RSM	Response surface methodology
FOE_M	Modified first-order equation
ANN	Artificial neural network
BP	Backpropagation
BR	Bayesian regularization
LM	Levenberg–Marquardt
AE	Absolute error (%)
MAE	Mean absolute error (%)
MSE	Mean square error (%)

List of symbols

v	Cutting speed (m/min)
f	Feed rate (mm/rev)
d	Depth of cut (mm)
F_c	Cutting force (N)
S	Sound pressure level (Pa)
V_v	Vibration velocity of workpiece (m/s)
n	Number of experiments
R_{ai}	Average of measured surface roughness in µm
$\hat{R}_{ai}$	Estimated surface roughness
h	Number of neurons in single hidden layer
R^2	Correlation coefficient

1 Introduction

Surface roughness (R_a) is a main performance indicator in machining, and it is important for different applications [1]. The existence of R_a is very complicated and method oriented. Machining can be modelled and confirmed for real-time control of the process to acquire the desired R_a [2], where modelling is the process of fitting input and output data [3]. Therefore, numerical models offering relationship amongst R_a and cutting parameters such as cutting speed, feed and depth of cut are developed [4–6].

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Nickel-based super alloy (Inconel 718) is most popular in aerospace, petroleum, medical industries, etc. though it is costly and difficult to machine [7–12]. Researchers have used regression analysis and response surface methodology (RSM) [13–22] for prediction of R_a. Deshpande et al. [2] have used regression-based modelling for estimating R_a in turning of Inconel 718. This paper deals with use of artificial neural network (ANN) for predicting R_a, and therefore, some works reporting use of ANN in machining of different alloys are discussed below.

Pontes et al. [15] predicted R_a using radial basis function neural network approach in hard turning of AISI 52100 steel. They concluded that the ANN model was accurately predicting the R_a. Mia and Dhar [16] used ANN for prediction of R_a and found excellent prediction accuracy with minimum root mean square error of 0.0284. Karayel [17] predicted R_a using ANN and used a control circuit for altering the cutting parameters to get specific R_a. Asiltürk and Çunkaş [18] used multiple regression and ANN with different training algorithms for estimation of R_a. The detailed analysis in the use of ANN modelling is tabulated in Table 1. It is observed that ANN model could be utilized successfully to predict the R_a compared to multiple regression model.

Furthermore, researchers have used cutting parameters along with cutting forces, tool vibrations, etc. as input for estimation of R_a [23–25]. They used multiple regression and ANN techniques in machining of different alloys. It is found that using ANN approach, R_a is predicted more accurately than regression analysis when responses are combined with cutting parameters. They also concluded that responses are useful for process monitoring.

As reported by Deshpande et al. [2], attaining good finish is very tough for Inconel 718. Hence, authors have reported very extensive statistical study for estimating regression-based R_a models. Due to enormous statistical calculation of used method [2], it was thought to apply some pattern classifier technique such as ANN. ANN is a soft computing method commonly used in several applications such as forecasting, data control and recognition of pattern. ANN is an effective tool used for estimation of response factors by considering its easiness, speed and learning ability [18]. Therefore, to confirm the results obtained by Deshpande et al. [2], it was decided to use ANN to the experimental data.

ANN consists of input, hidden and output layers. The input and output layers are defined as nodes, and the hidden layer provides an association amongst them. The accuracy and efficiency of ANN structure depend on network pattern, training algorithm, training data pattern, learning rate, processing function, testing data pattern and output data representation [16, 26]. The network gives the sets of patterns to be learned and the preferred system response for each pattern. It can be reconstructed to obtain minimum error [27]. Risbood et al. [24] and Upadhyay et al. [25] have used LM algorithm along with back propagation to train the single hidden layer network for prediction of R_a. The multi-layer perceptron (MLP) network requires less number of data points for training and testing of the network. Therefore, researchers have used MLP neural network in almost all machining processes. They found efficient performance of network model [24, 28, 29]. Risbood et al. [24] used neural network to predict R_a in turning using data of 26 experiments for training and testing. Tamang and Chandrasekaran [28] used data of 22 experiments for training and 5 for validation. Kohli and Dixit [29] have proposed an MLP neural network to predict R_a in turning process using data of 30 experiments for training and testing, and they predicted acceptable results. According to Hagan and Menhaj [30], the LM algorithm runs more rapidly when it trains with the feed forward neural network.

However, there is no study found on estimation of R_a using ANN approach in machining of Inconel 718 by combining input and response parameters. Hence, the goal of this work is to employ ANN for prediction of R_a in turning of Inconel 718 and compare the results with previously published results of regression analysis [2].

2 Experimentation

Inconel 718 bars, 120 mm long with 22 mm diameter, were machined for uncoated with untreated (UT) and cryogenically treated (CT) tungsten carbide (WC) inserts using minimum quantity lubrication (MQL) along with selected cutting conditions. Authors have already reported the details of experimentation in previous study [2].

MTAB CNC lathe machine was used for turning of Inconel 718 and is shown in Fig. 1. The piezoelectric dynamometer (make: Kistler, type: 9257B) was used for measurement of cutting forces (F_c). Microphone probe (GRAS's 40PH CCP) was used to measure sound pressure level (S) in Pascal (Pa). The signals from dynamometer and microphone were acquired with National Instrument's DAQ 9178. Laser digital vibrometer (make: Polytech, PDV-100) was used for measurement of vibration velocity (V_v) of workpiece (m/s). After completion of all experiments, the R_a on machined parts was measured with portable R_a tester (make: Mitutoyo, SURFTEST SJ-410). R_a was measured at three positions, 120° apart, along circumference of work piece. The average values of R_a were used for further analysis [2].

In [2], the central composite design (CCD) of RSM was used to design the experiments. The three input machining parameters—cutting speed (v), feed (f) and uncut

Table 1 Application of ANN modelling for prediction of surface roughness [15–18]

References	Workpiece material	Operation	Tool used	Parameters considered	Model used	Prediction accuracy based on	Remark
Pontes et al. [15]	AISI 52100 steel	Turning	Ceramic (Al_2O_3 + TiC) inserts	Speed, feed and depth of cut	ANN	Mean absolute percentage error and percentage of maximum error	The use of DOE method in the use of ANN architecture to be an effective tool for estimation of surface roughness
Mia and Dhar [16]	EN 24T steel	Dry turning	Coated carbide (TiCN, WC, Co) inserts	Speed, feed, hardness, dry and high-pressure coolant (HPC)	ANN with different training methods	Root mean square error (RMSE) and correlation coefficient (*R*-value)	The performance of the surface roughness is investigated for dry and HPC conditions. The Bayesian regularization proved the excellent prediction accuracy
Asiltürk and Çunkaş [18]	AISI 1040 steel	Dry turning	Coated carbide (TiCN, Al_2O_3) inserts	Speed, feed and depth of cut	Multiple regression and ANN with different training methods	Mean absolute percentage error and the determination coefficient (R^2)	R^2 for multiple regression models is 98.9%. The proposed model of ANN utilized successfully to predict the surface roughness compared to multiple regression
Karayel [17]	St. 50.2 steel	Turning	Carbide inserts	Speed, feed and depth of cut	ANN	Average absolute error	Surface roughness can be controlled by the designed control circuit to certain accuracy by altering the cutting parameters

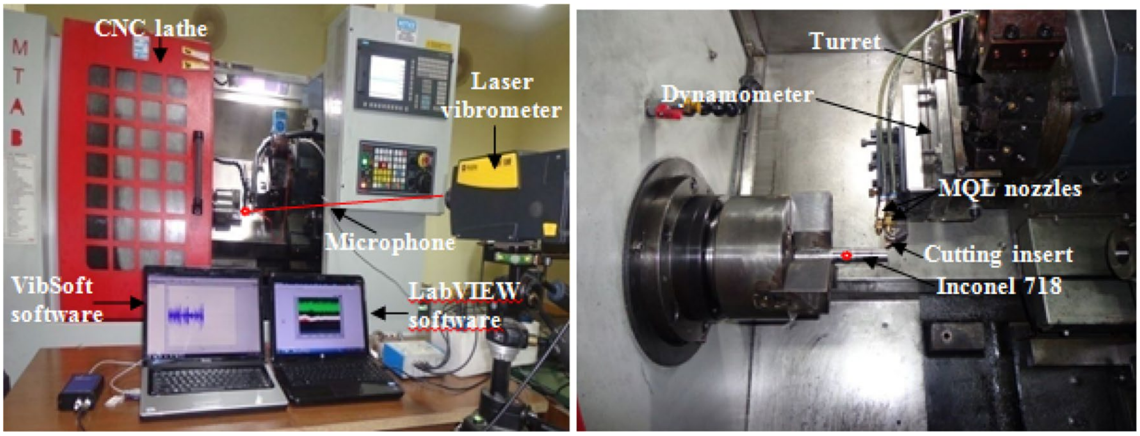


Fig. 1 Experimental setup (left) and turning of Inconel 718 (right) [2]

chip thickness (d)—were selected as input for design of experiment (DOE). The input design matrix and measured responses are presented in Table 2 for convenience of the readers. Based on data of Table 2, regression-based models were established for prediction of R_a. Modified first-order regression equations (FOE_M) were established using only significant input and response parameters [2] as shown in Eqs. (1) and (2) for untreated and cryogenically treated inserts, respectively. These equations were validated on the basis of coefficients of determination (R^2), mean absolute error (MAE) and mean square error (MSE). For comparing models (1–2) with ANN-based models, same experimental data (Table 2) are used. Use of ANN for prediction of R_a model is discussed in next section.

$$\hat{R}_a = 4.47 - 0.0381v + 9.95f - 2.03 \times 10^{-3}F_c - 0.023S - 481V_v \quad (R^2 = 91.5\%)(R^2\text{adj} = 88.4\%) \tag{1}$$

$$\hat{R}_a = 2.52 - 0.0259v + 8.04f + 0.582d - 3.87 \times 10^{-3}F_c + 0.365S + 166V_v \quad (R^2 = 94.8\%)(R^2\text{adj} = 92.3\%) \tag{2}$$

Table 2 Input design matrix and measured responses [2]

Run order	v (m/min)	f (mm/rev)	d (mm)	(Untreated/cryo-treated)			
				F_c (N)	S (Pa)	$V_v \times 10^{-4}$ (m/s)	R_a (µm)
1	90	0.18	1.07	200/190	0.270/0.260	13/12	1.78/1.79
2	9.5	0.115	0.785	617/602	0.794/0.780	37/36	2.30/2.40
3	30	0.18	0.5	463/456	0.531/0.633	33/23	2.20/2.20
4	60	0.01	0.785	231/225	0.210/0.209	16/15	0.99/1.00
5	60	0.115	0.785	455/445	0.472/0.462	26/25	0.93/0.99
6	60	0.115	1.264	404/390	0.501/0.487	23/24	1.49/1.80
7	110.45	0.115	0.785	163/160	0.190/0.189	13/13	0.62/0.60
8	30	0.18	1.07	590/580	0.791/0.781	36/35	2.20/2.30
9	60	0.115	0.785	459/551	0.660/0.652	27/25	0.93/0.98
10	60	0.115	0.785	461/555	0.691/0.686	29/26	0.99/0.95
11	90	0.18	0.5	279/270	0.130/0.123	19/17	1.25/1.21
12	90	0.05	1.07	190/185	0.198/0.192	12/11	0.52/0.75
13	60	0.224	0.785	444/440	0.509/0.491	32/30	2.40/2.50
14	60	0.115	0.785	464/461	0.521/0.511	28/27	0.99/1.10
15	30	0.05	1.07	447/442	0.422/0.412	29/28	1.60/1.60
16	30	0.05	0.5	436/432	0.421/0.419	27/26	1.90/1.36
17	60	0.115	0.785	471/476	0.567/0.559	28/26	0.92/1.10
18	60	0.115	0.305	300/295	0.321/0.312	26/24	1.30/1.35
19	60	0.115	0.785	451/445	0.563/0.558	30/29	0.93/1.17
20	90	0.05	0.5	150/147	0.161/0.158	12/11	0.72/0.76

3 Application of ANN

In this study, a multi-layer feed forward ANN structure trained with an error BP algorithm is employed to estimate R_a. The various ANN parameters have been selected by referring research papers because no standard procedure is found to define the architecture. Similarly, the number of neurons in hidden layer is obtained by trial-and-error approach by inspecting and comparing different architectures [15, 31]. ANN models are developed using function 'nntool' in MATLAB R2015a. 5-h-1 network pattern is used for untreated inserts with v, f, F_c, S, V_v as inputs and R_a as output. In the previous study [2], it was reported that Pearson correlation analysis (PCA) for depth of cut was found to be very close to zero; which indicated insignificant effect on R_a. So, depth of cut was removed in the case of untreated inserts. However, significant effect of depth of cut on R_a was found in the case of treated inserts. Therefore, 6-h-1 pattern is used which includes v, f, d, F_c, S, V_v as inputs and R_a as output for the cryo-treated inserts.

A single hidden layer with suitable number of neurons is selected using trial-and-error method. The design structures of network pattern are shown in Fig. 2 for both types of inserts. The neural networks are trained with LM learning algorithm using adaption learning function (LEARNGDM) and the tangent of sigmoid function.

With the aim, to improve the estimation accuracy of R_a in ANN, a total data of 150 sets (75 sets for untreated and 75 sets for treated) is generated using cutting parameters other than used in main experiment but within the range (Table 2). The data are obtained by varying one input parameter and keeping mid-values of other two input parameters constant and vice versa. Therefore, for untreated inserts, the estimated data of force, sound and vibration are obtained by placing cutting parameters in corresponding response equations published in Deshpande et al. [2]. R_a is estimated by inserting values of cutting parameters besides force, sound and vibration in Eq. (1). Similarly, data are generated for treated inserts, and the R_a is estimated using Eq. (2).

The data of 150 sets for untreated and treated inserts are imported in MATLAB R2015a workspace from Excel spreadsheet which can be directly used for ANN modelling. From the generated data of both inserts, 80% are used for training and testing is done with remaining 20% of data. The training parameters and all R^2 values obtained are mentioned in Table 3. Regression plots are showing estimated R_a on y-axis and experimental R_a on x-axis in Fig. 3. R^2 values of neural network model are found as

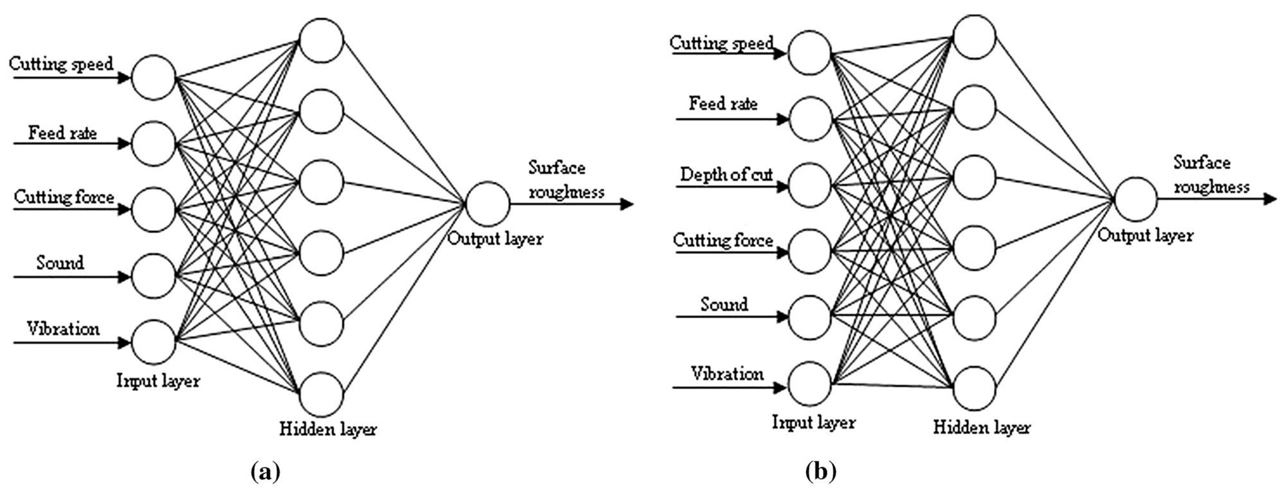
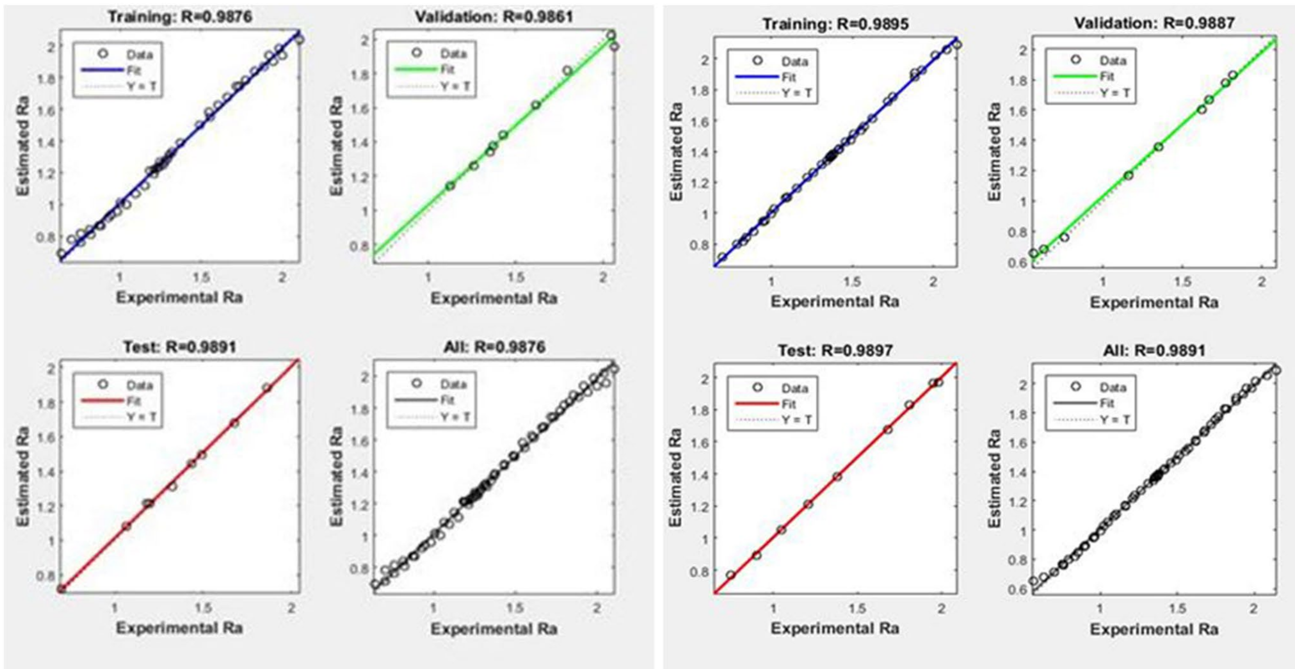


Fig. 2 Design structures of network pattern **a** 5-h-1 network pattern for untreated inserts **b** 6-h-1 network pattern for cryo treated inserts

Table 3 ANN training parameters for untreated and cryo-treated inserts

Parameters	Untreated inserts	Cryo-treated inserts
Neurons in the single hidden layer (h)	12 numbers	12 numbers
Epochs (frequency of progress displays)	4 iterations	8 iterations
Selection of maximum epochs to train	1000 numbers	1000 numbers
Maximum validation set	100 numbers	100 numbers
Sum-squared error goal	1×10^{-2}	1×10^{-2}
All R^2 values	98.76%	98.91%



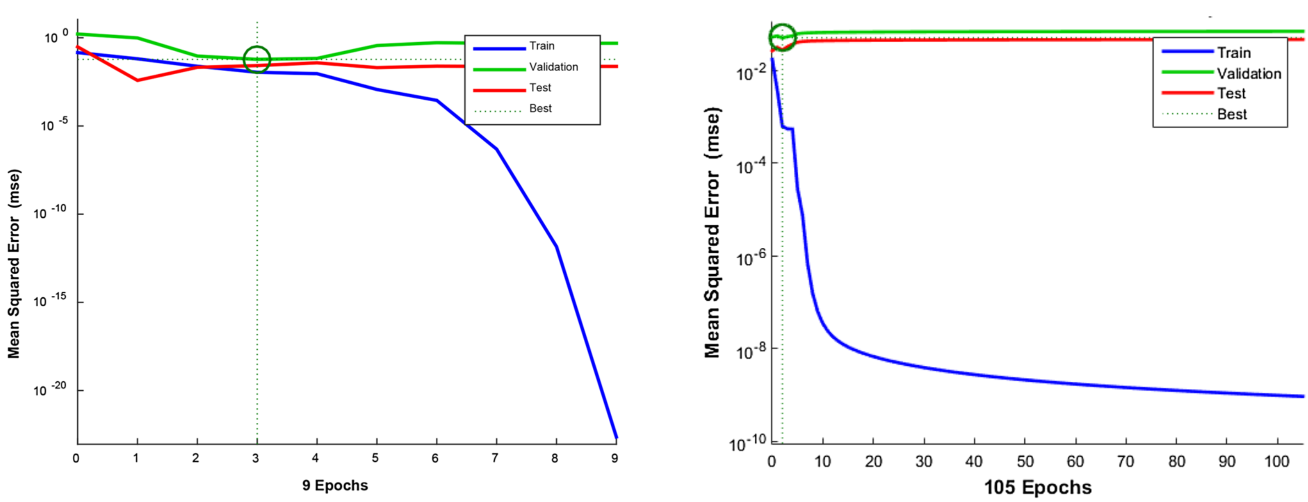
(a) (b)

Fig. 3 ANN regression plots **a** Untreated inserts **b** Cryo treated inserts

98.76% and 98.91% for untreated and treated inserts, respectively, which indicate very fine association and good fit as demonstrated in Fig. 3.

In addition to the above, to check the performance of ANN, performance curves are plotted for the two networks (for treated and untreated inserts) as shown in Fig. 4. The validation and the test curves continue together. There is no problem observed as regards to the fitting of both the curves, and hence using data of experiments does not seem to be an issue in the use of ANN during testing. After testing, MAE and MSE are found as 4.93%, 3.89% and 1.24%, 1.09% for treated and untreated inserts, respectively. Thus, good conformity can be observed between generated and estimated data of R_a using ANN.

Furthermore, seven additional experiments for each insert type are used for validation. The estimated R_a values, MAE and MSE obtained, are shown in Table 4. It is seen that percentage values of MAE are 7.30% and 9.14% for treated



(a) Untreated inserts **(b)** Cryo treated inserts

Fig. 4 ANN performance plots

Table 4 Performance of ANN in prediction of surface roughness

v (m/min)	*f* (mm/rev)	*d* (mm)	(Untreated/cryo-treated)						
			F_c (N)	*S* (Pa)	$V_v \times 10^{-4}$ (m/s)	R_a (µm)	ANN		
							$\hat{R}_a$ (µm)	AE (%)	SE (%)
10	0.12	0.79	600/698	0.74/0.77	35/36	2.20/1.98	2.15/1.82	2.27/8.08	0.25/2.56
60	0.12	0.79	450/410	0.455/0.52	26/29	1.30/1.32	1.16/1.11	10.77/15.91	1.96/4.41
80	0.10	0.70	275/290	0.294/0.30	19/18	1.00/1.10	1.02/0.98	2/10.91	0.04/1.44
110	0.12	0.79	158/149	0.215/0.14	11/27	0.60/0.83	0.66/0.71	− 10.00/14.46	0.36/1.44
60	0.22	0.79	445/436	0.51/0.25	32/20	2.10/1.77	1.92/1.83	8.57/− 3.39	3.24/0.36
45	0.11	0.78	400/500	0.59/0.60	28/25	1.80/1.50	1.72/1.63	4/8.67	0.64/1.69
60	0.12	1.26	398/377	0.49/0.27	29/28	1.30/1.56	1.47/1.60	− 13.08/− 2.56	2.89/0.16
Mean								7.30/9.14	1.34/1.72

and untreated inserts. Similarly, percentage values of MSE are 1.34% and 1.72% for both types of inserts. Therefore, the developed ANN models can be successfully used for estimation of in-process R_a for turning of Inconel 718 using carbide inserts.

4 Model comparisons

The prediction results of modified regression model are compared with ANN results as shown in Table 5. The R^2 values for training of neural network model are higher than modified regression models for both types of inserts, which mean that ANN models are better than regression. Based on R^2, MAE and MSE values, it is seen that modified regression and ANN models are able to predict R_a with more than 90% accuracy.

5 Conclusions

The paper has presented multiple regression and ANN-based models by considering untreated and cryogenically treated carbide inserts for turning of Inconel 718. These models revealed different degrees of fitness. Therefore, to recommend the best model for estimation of R_a, analysis of the estimated results and related error investigation has been performed. In the previous study, authors have established multiple regression analysis to estimate R_a with desirable accuracy. R^2 values of the modified regression model were obtained as 91.5% and 94.8%, and it indicates that the models can describe 91.5% and 94.8% of whole deviations in R_a for the untreated and treated inserts, respectively. Therefore, it is reported in the earlier study that using combination of specific cutting and response parameters, a good association was established amongst estimated and experimental data.

ANN prediction tool is proposed to test established regression models, 150 data sets are used for two types of inserts. ANN was trained and tested using combination of cutting and response parameters. All R^2 values are found as 98.76% and 98.91% for untreated and treated inserts, respectively, which indicate very fine association and good fit for both types of inserts. Improvement in R^2 values for training of neural network model for untreated and treated inserts indicates that ANN models are better for prediction than regression models. Furthermore, the regression plots of ANN confirm the fine association of fit between measured and estimated R_a. ANN performance was validated with independent data, which showed percentages of MAE are 7.30% and 9.14% for untreated and treated inserts, respectively. Similarly, percentages of MSE are 1.34% and 1.72% for the two cases. Therefore, the developed ANN models can be successfully used for estimation of in-process R_a.

It is found that modified regression model estimated R_a with more than 90%, whereas ANN is estimating

Table 5 Comparison of the models

Inserts type	Modified multiple regression model (FOE_M)					ANN model		
	Main expt. data			Confirmation test		Training all R^2 (%)	Confirmation test	
	R^2 (%)	MAE (%)	MSE (%)	MAE (%)	MSE (%)		MAE (%)	MSE (%)
Untreated	91.5	9.82	2.88	8.37	1.69	98.76	7.30	1.34
Treated	94.8	8.29	1.69	10.71	2.18	98.91	9.14	1.72

roughness more than 98%, based on R^2 values. Hence, it can be concluded that ANN is a better prediction tool for in-process monitoring of R_a for both the types of inserts. Such predictions can be useful for real-time control of the process to acquire the desired R_a.

6 Summary

In present research work, authors have proposed ANN modelling technique in turning of Inconel 718 (nickel-based supperalloy) using cryogenically treated and untreated carbide inserts. In this work, an attempt has been made to model, examine and compare the results of previously reported study, published by same authors with proposed ANN application.

The results of regression modelling technique are compared and analyzed using ANN application. The results obtained by ANN modelling using cutting parameters, force, sound and vibration are discussed for estimation of surface quality for treated and untreated inserts. This is the novelty of the article. Moreover, these results can be helpful to the machinist to attain good surface texture in finish cut for precision machining in modern era.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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