Applied Mathematical Modelling 36 (2012) 1477–1492

Contents lists available at SciVerse ScienceDirect

Applied Mathematical Modelling

journal homepage: www.elsevier.com/locate/apm

Regression and ANN models for estimating minimum value of machining performance

Azlan Mohd Zain [a,*], Habibollah Haron [a], Sultan Noman Qasem [a], Safian Sharif [b]

[a] Soft Computing Research Group, Faculty of Computer Science and Information Systems, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor, Malaysia
[b] Department of Manufacturing and Industrial Engineering, Faculty of Mechanical Engineering, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor, Malaysia

ARTICLE INFO

Article history:
Received 1 September 2010
Received in revised form 27 August 2011
Accepted 1 September 2011
Available online 8 September 2011

Keywords:
Modeling
Regression
ANN
Minimum surface roughness
End milling

ABSTRACT

Surface roughness is one of the most common performance measurements in machining process and an effective parameter in representing the quality of machined surface. The minimization of the machining performance measurement such as surface roughness (R_a) must be formulated in the standard mathematical model. To predict the minimum R_a value, the process of modeling is taken in this study. The developed model deals with real experimental data of the R_a in the end milling machining process. Two modeling approaches, regression and Artificial Neural Network (ANN), are applied to predict the minimum R_a value. The results show that regression and ANN models have reduced the minimum R_a value of real experimental data by about 1.57% and 1.05%, respectively.

1. Introduction

The developed model for the machining process is a mathematical equation that shows the relationship between two parameters, process parameters (decision variables) and machining performance (responses). Fundamentally, models can be divided into three categories which are experimental models, analytical models and Artificial Intelligent (AI) based models. Experimental and analytical models can be developed by using conventional approaches such as Regression technique. While, AI based models are developed using non-conventional approaches such as Artificial Neural Network (ANN).

The difference between the regression model and ANN lies mainly in the nonlinear regions [1]. ANNs can be used as an effective and an alternative method for the experimental studies whose the mathematical model cannot be formed [2]. Regression technique may work well for machining process modeling as reported by many previous studies. A mathematical model was developed using regression model for surface roughness in wire electrical discharge machining, and it was found that the developed model showed high prediction accuracy within the experimental region. The maximum prediction error of the model was less than 7%, and the average percentage error of prediction was less than 3% [3]. The regression model showed a slightly better performance compared to the ANN model for modeling surface roughness in abrasive waterjet machining [4]. However, regression model may not precisely described the underlying non linear complex relationship between decision variables and responses [5]. ANN and Regression models are used to model the surface roughness and tool wear machining performance in hard turning machining [6]. As a result, the ANN models provided better prediction capabilities because they generally offer the ability to model more complex nonlinearities and interactions than linear and exponential regression models can offer. ANN model follows the machining experimental data much more closely than that from regression model [1].

* Corresponding author. Tel.: +60 7 5532088; fax: +60 7 5565044/5574908.
E-mail addresses: azlanmz@utm.my, azlanmz6674@gmail.com (A.M. Zain).

0307-904X/$ - see front matter
doi:10.1016/j.apm.2011.09.035

The literatures show that surface roughness (R_a) is one of the performance measures studied mostly by researcher in modeling problem. Some recent studies deal with ANN for modeling surface roughness in various machining operations such as wire electrical discharge machining [7,8], turning [9–12], and milling [13–18]. With Regression and ANN as the considered modeling techniques, the objective of this paper is to study the prediction result for surface roughness performance measure in end milling machining operation. ANN model gave a high accuracy rate (96–99%) for predicting machining performance (surface roughness) in end milling operation compared to the result obtained from regression model [19]. It was reported that the minimization of R_a machining performance in end milling involving radial rake angle process parameter is still lacking, in particular when dealing with titanium alloys. As such optimization of the cutting conditions, which include radial rake angle, combined with cutting speed and feed, for the R_a in end milling of Ti–6Al–4V can be considered as a new contribution to the machining research.

2. Modeling of surface roughness

Modeling is described as a scientific way to study the behaviors involved in the process. Modeling of machining processes is important for providing the basis mathematical model for the formulation of the objective function. A model developed for machining process is the relationship between two variables which are decision variable and response variable in terms of mathematical equations. Therefore, the minimization of the R_a must be formulated in the standard mathematical model. Normally, the model of the predicted R_a can be expressed as in Eq. (1):

$$R_a = k\prod_{i=1}^{n} c_i^{e_i}. \tag{1}$$

Eq. (1) can also be written as follows:

$$R_a = kc_1^{e_1}c_2^{e_2}c_3^{e_3}\cdots c_n^{e_n}, \tag{2}$$

where R_a is the predicted surface roughness (respond variable), $c_1\cdots c_n$ is the cutting conditions (decision variables), and k, $e_1, e_2, e_3, \ldots, e_n$ are the model parameters to be estimated using the experimental data.

In the milling process, material is removed from the workpiece by a rotating cutter. The milling process can be classified into two parts; peripheral milling and face milling. Peripheral milling generates a surface parallel to the spindle rotation, while face milling generates a surface normal to the spindle rotation. End milling is a type of face milling, and is used for facing, profiling and slotting processes. Fig. 1 shows an illustration of interaction between cutting tool and workpiece for removing material in the end milling process.

In the end milling process, the surface can be generated by two methods; up milling and down milling. Up milling is also called conventional milling; the cutter rotates against the direction of feed of the workpiece. Down milling is also called climb milling; the rotation is in the same direction as the feed. These processes are illustrated in Fig. 2.

A machining experiment was conducted based on the down milling process [20]. A mathematical model of the predicted R_a is expressed in Eq. (3)

$$R_a = kv^{e_1}f^{e_2}\gamma^{e_3}, \tag{3}$$

where R_a is the predicted surface roughness in µm, v is the cutting speed in m/min, f is the feed rate in mm/tooth, γ is the radial rake angle in °, and k, e_1, e_2 and e_3 are the model parameters to be estimated using the experimental data.

2.1. Regression modeling

To develop the regression model for estimating the R_a value, the mathematical model given in Eq. (3) is linearized by performing a logarithmic transformation as follows:

$$\ln R_a = \ln k + e_1 \ln c_1 + e_2 \ln c_2 + e_3 \ln c_3 + \cdots e_n \ln c_n. \tag{4}$$

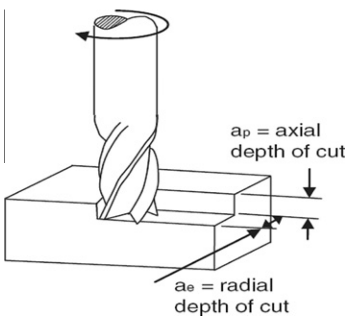

Fig. 1. Illustration of end milling process.

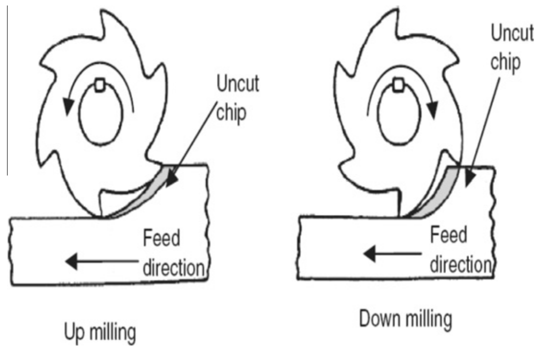

Fig. 2. Illustration of up and down milling processes.

Eq. (4) can also be rewritten as follows:

$$y = b_0x_0 + b_1x_1 + b_2x_2 + b_3x_3 \cdots b_nx_n, \tag{5}$$

where y is the logarithmic value of the experimental R_a, $x_0 = 1$ is a dummy variable, $x_1, x_2, \ldots, x_n$ are the cutting condition values (logarithmic transformations), and $b_0, b_1, b_2, \ldots, b_n$ are the model parameters to be estimated using the experimental data.

The regression model of the predicted R_a for end milling is expressed in Eq. (6) [20]

$$y = b_0 + b_1 v + b_2 f + b_3 \gamma, \tag{6}$$

where y is the logarithmic value of the experimental R_a in µm, v is the cutting speed in m/min, f is the feed rate in mm/tooth, γ is the radial rake angle in °, and b_0, b_1, b_2 and b_3 are the model parameters to be estimated using the experimental data.

2.2. ANN modeling

An illustration of the ANN structure used to develop a model for R_a is given in Fig. 3.

From Fig. 3, considering the multilayer feedforward training network with one hidden layer is applied, the net input to unit k in the hidden layer is expressed in Eq. (7)

$$net\_hidden = \sum_{j=1}^{J} C_{j,k} i_j + \theta_k, \tag{7}$$

where J is number of nodes of the input layer, $C_{j,k}$ is the weight between the input nodes and hidden nodes, i_j is the value of the input which consists of cutting conditions such as speed, feed rate and rake angle of the experimental sample, and θ_k is the biases on the hidden nodes.

Consequently, the net input to unit z in the output layer is expressed in Eq. (8)

$$net\_output = \sum_{k=1}^{K} D_{k,z} h_k + \phi_z, \tag{8}$$

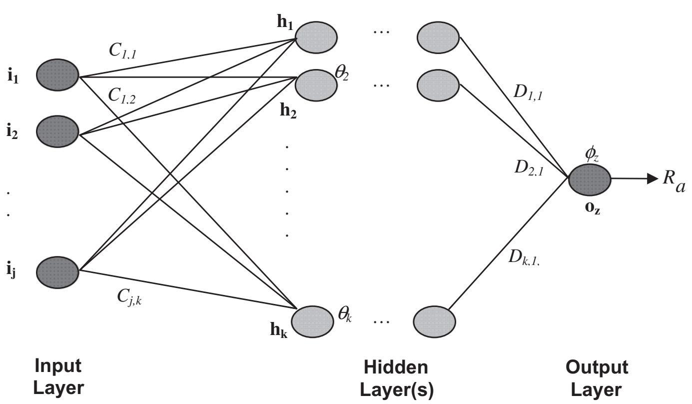

Fig. 3. Illustration of ANN structure.

where K is number of nodes of the hidden layer, $D_{k,z}$ is the weight between hidden and output nodes, h_k is the value of the output for hidden nodes, and ϕ_z is the biases on the output nodes.

From Eqs. (7) and (8), the output for hidden nodes can be given as Eq. (9), and the output for output nodes can be given as Eq. (10)

$$h_k = f(net\_hidden), \tag{9}$$

$$o_z = f(net\_output) = R_a, \tag{10}$$

where f is the transfer function to predict R_a value.

3. Experimental data of the case studies

The machining experiment by Mohruni [20] to measure the R_a value in the end milling was considered in this study. The work piece used in the experiments was an annealed alpha–beta titanium alloy, Ti–6Al–4V (Ti-64). The chemical composition of the Ti–6Al–4V are listed in Table 1. Three types of end mills were used in the experiments, namely uncoated carbide (WC-Co) and two TiAlN base coated carbide tools which include common PVD-TiAlN coated carbide tool and PVD with enriched Al-content TiAlN coated carbide tools (also called Supernitride coating or SN_{TR}). The composition and properties of these cutting tools are illustrated in Table 2.

3.1. Experimental design

Three cutting conditions are considered for end milling machining process. They are cutting speed, feed rate and radial rake angle. Experimental design for the end milling process is given in Table 3. From this table, the five levels of cutting condition of experimental design are −1.4142, −1, 0, +1 and +1.4142. The whole experiments were carried out under flood conditions (6% concentration of water base coolants) with 5 mm constant axial depth of cut and 2 mm constant radial depth of cut.

Table 1
Chemical composition of Ti–6Al4V.

Al	6.37
V	3.89
Fe	0.16
C	0.002
Mo	<0.01
Mn	<0.01
Si	<0.01
Ti	Balance

Table 2
Properties of the cutting tool used in the experiments.

Tool type		Uncoated	TiAlN coated	SN_{TR} coated
Substrate (wt%)	WC	94	94	94
	Co	6	6	6
Properties	Grade	K30	K30	K30
	Grain size (μm)	0.5	0.5	0.5
Coating	Process	–	PVD-HIS	PVD-HIS
	Coating thickness	–	Monolayer (3–4 μm)	Multilayer (1–8 μm)
	Film composition (mol-%AIN)	–	Approx. 54	Approx. 65–67

Table 3
Levels of cutting condition for end milling.

Cutting conditions	Units	Levels				
		−1.4142	−1	0	+1	+1.4142
Cutting speed, v	m/min	124.53	130.00	144.22	160.00	167.03
Feed rate, f	mm/tooth	0.025	0.03	0.046	0.07	0.083
Radial rake angle, γ	°	6.2	7.0	9.5	13.0	14.8

3.2. Experimental results

A total of 24 experimental trials were executed based on eight data of two levels DOE 2^k full factorial, four center and twelve axial points. All R_a values were collected during actual machining for the three type of cutting tools, uncoated, TiA1N coated and SN_{TR} coated cutting tools, are shown in Table 4.

4. Development of regression model

Regression models for each cutting tool are developed using SPSS software based on the experimental data given in Table 4. The coefficients value of modeled independent variable for uncoated, TiA1N coated and SN_{TR} coated cutting tools are given in Tables 5–7, respectively.

By transferring the coefficients value of independent variable (Tables 5–7) into Eq. (6), the regression model for each cutting tool could be written as follows:

$$\hat{y_1} = \hat{R}_a\text{\_uncoated} = 0.451 - 0.00267x_1 + 5.671x_2 + 0.0046x_3, \tag{11}$$

$$\hat{y_2} = \hat{R}_a\text{\_TiA1N} = 0.292 - 0.000855x_1 + 5.383x_2 - 0.00553x_3, \tag{12}$$

$$\hat{y_3} = \hat{R}_a\text{\_SN}_{TR} = 0.237 - 0.00175x_1 + 8.693x_2 - 0.00159x_3 \tag{13}$$

Eqs. (11)–(13) are used to calculate the predicted R_a values, and the results are summarized in Table 8. Then, R_a values of the experimental data (Table 4) and the predicted R_a values of regression model (Table 8) are compared. The line pattern data of R_a real machining vs. predicted R_a regression model in shown in Fig. 4.

Table 4
Experimental R_a values for end milling.

No.	Data source	Setting values of experimental cutting conditions			Experimental R_a value (μm)		
		v (m/min)	f (mm/tooth)	γ (°)	$R_{a\_uncoated}$	R_{a_TiA1N}	$R_a\_SN_{TR}$
1	DOE 2^k	130	0.03	7	0.365	0.32	0.284
2		160	0.03	7	0.256	0.266	0.196
3		130	0.07	7	0.498	0.606	0.668
4		160	0.07	7	0.464	0.476	0.624
5		130	0.03	13	0.428	0.260	0.280
6		160	0.03	13	0.252	0.232	0.190
7		130	0.07	13	0.561	0.412	0.612
8		160	0.07	13	0.512	0.392	0.576
9	Center	144.22	0.046	9.5	0.464	0.324	0.329
10		144.22	0.046	9.5	0.444	0.380	0.416
11		144.22	0.046	9.5	0.448	0.460	0.352
12		144.22	0.046	9.5	0.424	0.304	0.400
13	Axial	124.53	0.046	9.5	0.328	0.360	0.344
14		124.53	0.046	9.5	0.324	0.308	0.320
15		167.03	0.046	9.5	0.236	0.340	0.272
16		167.03	0.046	9.5	0.240	0.356	0.288
17		144.22	0.025	9.5	0.252	0.308	0.230
18		144.22	0.025	9.5	0.262	0.328	0.234
19		144.22	0.083	9.5	0.584	0.656	0.640
20		144.22	0.083	9.5	0.656	0.584	0.696
21		144.22	0.046	6.2	0.304	0.300	0.361
22		144.22	0.046	6.2	0.288	0.316	0.360
23		144.22	0.046	14.8	0.316	0.324	0.368
24		144.22	0.046	14.8	0.348	0.396	0.360
R_a (minimum)					0.236	0.232	0.190

Table 5
Coefficients values for uncoated cutting tool.

Independent variable	Unstandardized coefficients		Standardized coefficients	T	Sig.
	B	Std. error	Beta		
(Constant)	0.451	0.175		2.582	0.018
Speed	−2.67E−03	0.001	−0.277	−2.407	0.026
Feed	5.671	0.811	0.805	6.994	0
Radial rake angle	4.60E−03	0.005	0.097	0.842	0.41

Table 6
Coefficients values for TiA1N coated cutting tool.

Independent variable	Unstandardized coefficients		Standardized coefficients	T	Sig.
	B	Std. error	Beta		
(Constant)	0.292	0.158		1.85	0.079
Speed	−8.55E−04	0.001	−0.098	−0.854	0.403
Feed	5.383	0.731	0.843	7.36	0
Radial rake angle	−5.53E−03	0.005	−0.129	−1.122	0.275

Table 7
Coefficients values for SN_{TR} coated cutting tool.

Independent variable	Unstandardized coefficients		Standardized coefficients	T	Sig.
	B	Std. Error	Beta		
(Constant)	0.237	0.116		2.042	0.055
Speed	−1.75E−03	0.001	−0.14	−2.368	0.028
Feed	8.693	0.539	0.954	16.143	0
Radial rake angle	−1.59E−03	0.004	−0.026	−0.437	0.667

Table 8
Predicted R_a values of end milling regression model.

No.	Data source	Experimental cutting conditions			Predicted R_a values (μm)		
		V (m/min)	f (mm/tooth)	γ (°)	$\hat{R}_{uncoated}$	$\hat{R}_{TiA1N}$	$\hat{R}_{SN_{TR}}$
1	DOE 2^k	130	0.03	7	0.306	0.304	0.259
2		160	0.03	7	0.226	0.278	0.207
3		130	0.07	7	0.533	0.519	0.607
4		160	0.07	7	0.453	0.493	0.554
5		130	0.03	13	0.334	0.270	0.250
6		160	0.03	13	0.254	0.245	0.197
7		130	0.07	13	0.561	0.486	0.597
8		160	0.07	13	0.481	0.460	0.545
9	Center	144.22	0.046	9.5	0.370	0.364	0.369
10		144.22	0.046	9.5	0.370	0.364	0.369
11		144.22	0.046	9.5	0.370	0.364	0.369
12		144.22	0.046	9.5	0.370	0.364	0.369
13	Axial	124.53	0.046	9.5	0.423	0.381	0.404
14		124.53	0.046	9.5	0.423	0.381	0.404
15		167.03	0.046	9.5	0.310	0.344	0.329
16		167.03	0.046	9.5	0.310	0.344	0.329
17		144.22	0.025	9.5	0.251	0.251	0.187
18		144.22	0.025	9.5	0.251	0.251	0.187
19		144.22	0.083	9.5	0.580	0.563	0.691
20		144.22	0.083	9.5	0.580	0.563	0.691
21		144.22	0.046	6.2	0.355	0.382	0.374
22		144.22	0.046	6.2	0.355	0.382	0.374
23		144.22	0.046	14.8	0.395	0.334	0.361
24		144.22	0.046	14.8	0.395	0.334	0.361
R_a (minimum)					0.226	0.245	0.187

As illustrated in Fig. 4, the three generated graphs for uncoated, TiA1N coated and SN_{TR} coated cutting tools gave a similar pattern for R_a values between the experimental data and regression model data. Therefore, the assumption could be made is that all cutting tools have given a good prediction in estimating the predicted R_a values.

In selecting the best regression model, a convenient approach is to evaluate all possible regression models [21]. In this study, the t test is conducted to determine the cutting tool that it deals with the best end milling regression model. The paired-sample t test using SPSS software was conducted to determine the best regression model and the results were summarized in Tables 9 and 10.

Table 9 shows that all three pairs of experimental data and regression modeling data are positively correlated, $r(N = 24) = 0.857$ for pair 1, $r(N = 24) = 0.859$ for pair 2, and $r(N = 24) = 0.965$ for pair 3. From Table 10, it can be seen that the mean R_a value for pair 1 increased from the experimental result to the uncoated regression model result by 0.0000833, $t(23) = -0.007$, $p = 0.995$. The 95% confidence interval ranges from −0.0264 to 0.0263 (including zero). Therefore, the two means of experimental result and regression model results are not significantly different from each other. The mean

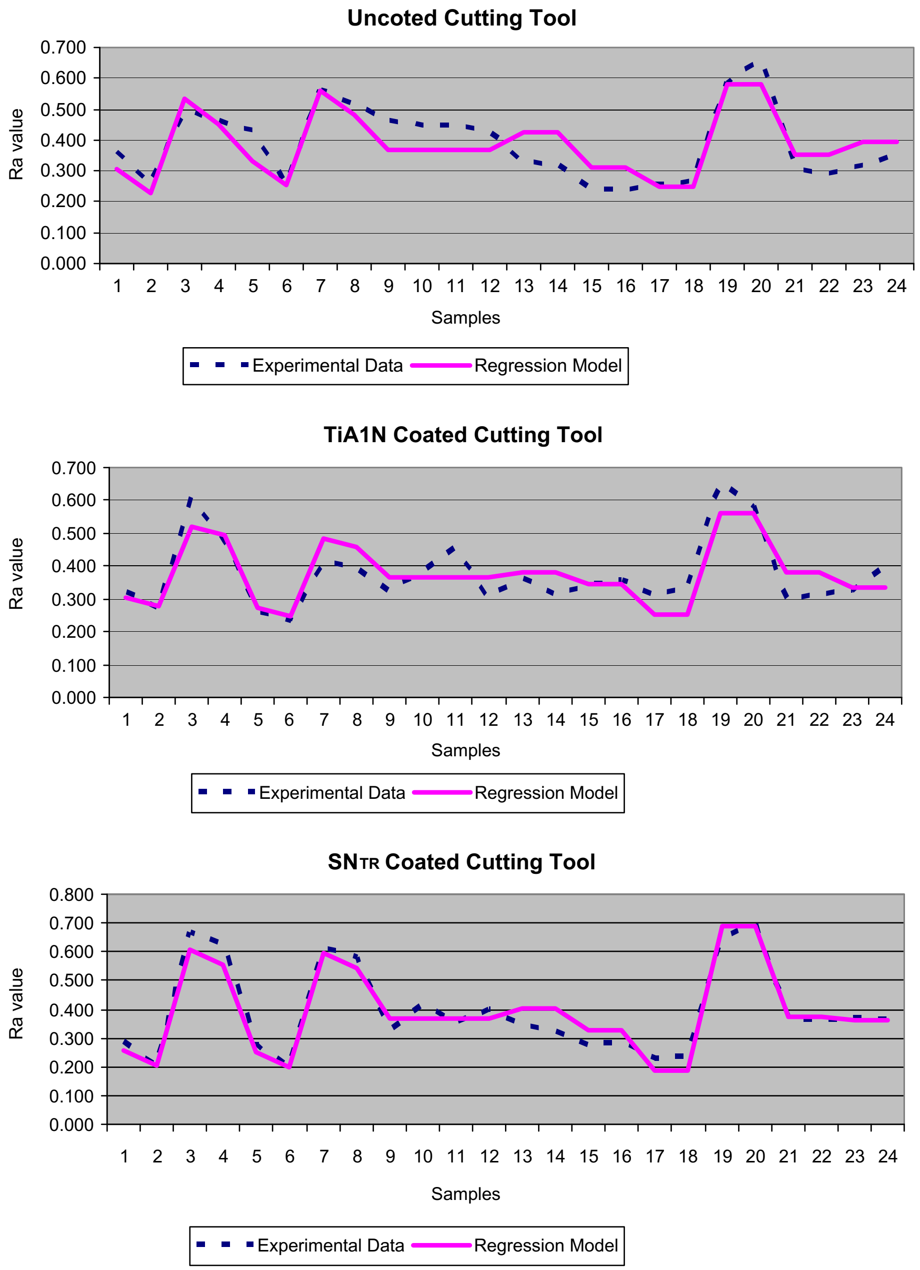

Fig. 4. Experimental vs. regression for R_a values.

Table 9
Statistics and correlations (experimental vs. regression).

	Variable	Mean	*N*	Std. deviation	Std. error mean	Correlation	Sig.
Pair 1	EXP_UNC	0.38558	24	0.12088	2.47E−02	0.857	0.000
	REG_UNC	0.38567	24	0.10363	2.12E−02		
Pair 2	EXP_TIAN	0.37533	24	0.10964	2.24E−02	0.859	0.000
	REG_TIAN	0.37587	24	9.42E−02	1.92E−02		
Pair 3	EXP_SN_{TR}	0.39167	24	0.1565	3.19E−02	0.965	0.000
	REG_SN_{TR}	0.39100	24	0.1509	3.08E−02		

R_a value for the pair 2 also increased from the experimental result to the TiA1N coated regression model result by 0.000542, $t(23) = -0.047$, $p = 0.963$. The 95% confidence interval ranges from −0.0243 to 0.0232 (including zero), which also proves

Table 10
Paired samples test (experimental vs. regression).

Pair		Paired differences					T	Df	Sig. (2-tailed)
		Mean	Std. deviation	Std. error mean	95% Conf. inter. of the difference				
					Lower	Upper			
Pair 1	EXP_UNC and REG_UNC	−8.33E−05	6.24E−02	1.27E−02	−2.64E−02	2.63E−02	−0.007	23	0.995
Pair 2	EXP_TIAN and REG_TIAN	−5.42E−04	5.62E−02	1.15E−02	−2.43E−02	2.32E−02	−0.047	23	0.963
Pair 3	EXP_SN_{TR} and REG_SN_{TR}	6.67E−04	4.13E−02	8.43E−03	−1.68E−02	1.81E−02	0.079	23	0.938

that the two means are not significantly different from each other. By looking at the pair 3 in Table 10, it can be seen that the mean R_a value however reduced from experimental result to the SN_{TR} coated regression model result by 0.000667, $t(23) = 0.079$, $p = 0.938$. The 95% confidence interval ranges from −0.0168 to 0.0181 (including zero). Therefore, the two means too are not significantly different from each other.

As a conclusion, based on the results of the paired-sample t test, it could be summarized that the SN_{TR} coated cutting tool has given the highest positive correlation and is the only pair that gave a reduced mean R_a value from the experimental result. Thus, it can be concluded that the predicted R_a equation of SN_{TR} coated cutting tools, Eq. (13), is proposed as optimi-

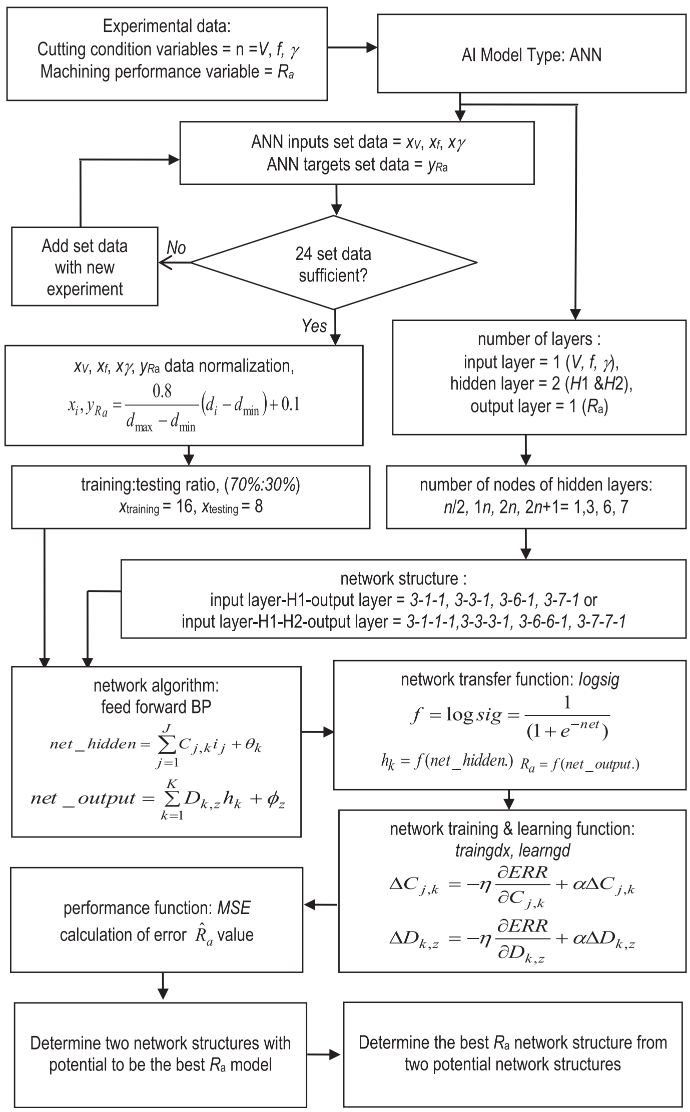

Fig. 5. Flow of the ANN model development for the R_a prediction.

zation objective function for end milling process. The minimum predicted surface roughness value of SN_{TR} coated cutting tool that is selected as the best regression model is 0.187 μm (the 17th and 18th row of Table 8). The cutting conditions values that lead to minimum predicted surface roughness value of SN_{TR} coated are: v = 144.22 m/min, f = 0.025 mm/tooth and $\gamma = 9.5^\circ$.

5. Development of ANN model

The eight selection influencing factors in developing the ANN model are given as follows:

(i) The ANN network structure to give the best prediction result.
(ii) The ratio of training and testing data for the developed ANN model.
(iii) The normalization of the input/output data made with the available experimental sample size data.
(iv) The network algorithm to give the best prediction result.
(v) The transfer function to give the best prediction result.
(vi) The performance functions to give a low error rate in the predicted value.
(vii) The training function to give a low error rate in the response value for the developed ANN model.
(viii) The learning function to give a low error rate in the response value for the developed ANN model.

Considering the eight influencing factors above, the flow of development of the ANN model for end milling is illustrated in Fig. 5.

Normalized machining cutting condition values are used as the inputs, and normalized machining performance value is used as the target in the modeling process. A normalization equation suggested by Sanjay and Jyothi [22] as given as follows:

$$x_i = \frac{0.8}{d_{\max} - d_{\min}}(d_i - d_{\min}) + 0.1 \tag{14}$$

Considering the normalization equation in Eq. (11), the normalized values for end milling experimental data are calculated and given in Table 11. From 24 normalized experimental sets of data, they will be separated into two groups which are training and testing set data. Four sets of center data (the 9th to 12th sets of experimental data) and twelve sets of axial data (the 13th to the last sets of experimental data), giving a total of 16 sets of data, were chosen as the training set data. DOE 2^k data (the first eight experimental data) with a total of eight sets of data will be used as the testing data.

With the ANN Matlab toolbox (learning rate = 0.01, and momentum rate = 0.05), the modeling result (surface roughness predicted value) for the training set data is summarized in Table 12. The MSE values for the testing set data is given in

Table 11
Normalized values of machining data.

No.	Data source	x_i			y_{R_a}		
		x_{speed}	x_{feed}	$x_{\text{rake angle}}$	$y_{R_a\text{\_uncoated}}$	$y_{R_a\text{\_TiA1N}}$	$y_{R_a\text{\_SN}_{TR}}$
1	DOE 2^k	0.203	0.169	0.174	0.346	0.266	0.249
2		0.768	0.169	0.174	0.138	0.164	0.109
3		0.203	0.721	0.174	0.599	0.806	0.856
4		0.768	0.721	0.174	0.534	0.560	0.786
5		0.203	0.169	0.733	0.466	0.153	0.242
6		0.768	0.169	0.733	0.130	0.100	0.100
7		0.203	0.721	0.733	0.719	0.440	0.767
8		0.768	0.721	0.733	0.626	0.402	0.710
9	Center	0.471	0.390	0.407	0.534	0.274	0.320
10		0.471	0.390	0.407	0.496	0.379	0.457
11		0.471	0.390	0.407	0.504	0.530	0.356
12		0.471	0.390	0.407	0.458	0.236	0.432
13	Axial	0.100	0.390	0.407	0.275	0.342	0.343
14		0.100	0.390	0.407	0.268	0.243	0.306
15		0.900	0.390	0.407	0.100	0.304	0.230
16		0.900	0.390	0.407	0.108	0.334	0.255
17		0.471	0.100	0.407	0.130	0.243	0.163
18		0.471	0.100	0.407	0.150	0.281	0.170
19		0.471	0.900	0.407	0.763	0.900	0.811
20		0.471	0.900	0.407	0.900	0.764	0.900
21		0.471	0.390	0.100	0.230	0.228	0.370
22		0.471	0.390	0.100	0.199	0.258	0.369
23		0.471	0.390	0.900	0.252	0.274	0.381
24		0.471	0.390	0.900	0.313	0.409	0.369
Minimum (R_a)					0.100	0.100	0.100

Table 12
Predicted values of ANN training.

No.	Data source	Uncoated								TiA1N coated								SN_{TR} coated							
		3–1–1	3–3–1	3–6–1	3–7–1	3–1–1–1	3–3–3–1	3–6–6–1	3–7–7–1	3–1–1	3–3–1	3–6–1	3–7–1	3–1–1–1	3–3–3–1	3–6–6–1	3–7–7–1	3–1–1	3–3–1	3–6–1	3–7–1	3–1–1–1	3–3–3–1	3–6–6–1	3–7–7–1
1	Center	0.069	0.185	0.348	0.291	0.224	0.406	0.417	0.409	0.255	0.334	0.160	0.342	0.229	0.387	0.372	0.296	0.308	0.366	0.519	0.317	0.081	0.387	0.385	0.412
2		0.069	0.185	0.348	0.291	0.224	0.406	0.417	0.409	0.255	0.334	0.160	0.342	0.229	0.387	0.372	0.296	0.308	0.366	0.519	0.317	0.081	0.387	0.385	0.412
3		0.069	0.185	0.348	0.291	0.224	0.406	0.417	0.409	0.255	0.334	0.160	0.342	0.229	0.387	0.372	0.296	0.308	0.366	0.519	0.317	0.081	0.387	0.385	0.412
4		0.069	0.185	0.348	0.291	0.224	0.406	0.417	0.409	0.255	0.334	0.160	0.342	0.229	0.387	0.372	0.296	0.308	0.366	0.519	0.317	0.081	0.387	0.385	0.412
5	Axial	0.033	0.328	0.277	0.225	0.197	0.481	0.346	0.441	0.565	0.576	0.449	0.043	0.474	0.390	0.463	0.157	0.769	0.425	0.057	0.006	0.057	0.457	0.317	0.297
6		0.033	0.328	0.277	0.225	0.197	0.481	0.346	0.441	0.565	0.576	0.449	0.043	0.474	0.390	0.463	0.157	0.769	0.425	0.057	0.006	0.057	0.457	0.317	0.297
7		0.362	0.454	0.295	0.276	0.357	0.241	0.095	0.031	0.118	0.284	0.333	0.609	0.130	0.390	0.247	0.438	0.088	0.302	0.150	0.648	0.267	0.355	0.509	0.412
8		0.362	0.454	0.295	0.276	0.357	0.241	0.095	0.031	0.118	0.284	0.333	0.609	0.130	0.390	0.247	0.438	0.088	0.302	0.150	0.648	0.267	0.355	0.509	0.412
9		0.262	0.240	0.027	0.255	0.189	0.283	0.247	0.456	0.098	0.232	0.157	0.319	0.127	0.457	0.374	0.135	0.104	0.640	0.159	0.254	0.427	0.386	0.330	0.097
10		0.262	0.240	0.027	0.255	0.189	0.283	0.247	0.456	0.098	0.232	0.157	0.319	0.127	0.457	0.374	0.135	0.104	0.640	0.159	0.254	0.427	0.386	0.330	0.097
11		0.028	0.524	0.648	0.653	0.889	0.383	0.615	0.337	0.902	0.469	0.670	0.432	0.762	0.325	0.406	0.801	0.877	0.220	0.461	0.567	0.051	0.333	0.464	0.759
12		0.028	0.524	0.648	0.653	0.889	0.383	0.615	0.337	0.902	0.469	0.670	0.432	0.762	0.325	0.406	0.801	0.877	0.220	0.461	0.567	0.051	0.333	0.464	0.759
13		0.127	0.101	0.578	0.528	0.211	0.404	0.013	0.436	0.227	0.388	0.640	0.138	0.101	0.406	0.540	0.218	0.422	0.294	0.731	0.117	0.238	0.409	0.174	0.231
14		0.127	0.101	0.578	0.528	0.211	0.404	0.013	0.436	0.227	0.388	0.640	0.138	0.101	0.406	0.540	0.218	0.422	0.294	0.731	0.117	0.238	0.409	0.174	0.231
15		0.038	0.624	0.066	0.076	0.262	0.266	0.890	0.059	0.310	0.100	0.277	0.447	0.876	0.305	0.330	0.525	0.183	0.219	0.009	0.834	0.053	0.332	0.468	0.432
16		0.038	0.624	0.066	0.076	0.262	0.266	0.890	0.059	0.310	0.100	0.277	0.447	0.876	0.305	0.330	0.525	0.183	0.219	0.009	0.834	0.053	0.332	0.468	0.432
Minimum (R_a)		0.028	0.101	0.027	0.076	0.189	0.241	0.013	0.031	0.098	0.100	0.157	0.043	0.101	0.305	0.247	0.135	0.088	0.219	0.009	0.006	0.051	0.332	0.174	0.097

Table 13
MSE values of ANN testing.

Data source	Cutting tool	Network structure	MSE values
DOE 2^k	Uncoated	3–1–1	0.087
		3–3–1	0.054
		3–6–1	0.128
		3–7–1	0.069
		3–1–1–1	0.055
		3–3–3–1	0.154
		3–6–6–1	0.041
		3–7–7–1	0.013
	TiA1N coated	3–1–1	0.126
		3–3–1	0.091
		3–6–1	0.166
		3–7–1	0.024
		3–1–1–1	0.032
		3–3–3–1	0.133
		3–6–6–1	0.051
		3–7–7–1	0.052
	SN_{TR} coated	3–1–1	0.134
		3–3–1	0.024
		3–6–1	0.092
		3–7–1	0.013
		3–1–1–1	0.208
		3–3–3–1	0.101
		3–6–6–1	0.043
		3–7–7–1	0.306

Table 13. The MSE plot results of Matlab optimization toolbox, with single hidden layer and two hidden layers of network structure, for each cutting tool are given in Figs. 6 and 7, respectively.

In order to determine the best ANN model, overall, four factors are given consideration and separated into two parts. The first part is determination of the network structure with potential to be the best ANN prediction model. The second part is determination of the best network structure from two potential network structures.

For the first factor, Fig. 8 shows six graphs which represent the line patterns of the data between the ANN targets and the ANN outputs for uncoated, TiA1N coated, and SN_{TR} coated for ANN model with single hidden layer and two hidden layers.

According to the graphs in Fig. 8, summary of the similarities in the line pattern criterion is given in the third column of Table 14. The forth column of Table 14 presents the result of the t test which gives the correlation value between the ANN targets and the ANN outputs which is the second factor to be considered in determining the two networks with the potential to be the best ANN model.

Supported by quite similar of the pattern line and the high positive correlation values, according to Table 14, it could be stated that the two networks with the potential to be the best ANN model are:

(i) The 3–7–7–1 network structure of TiA1N coated cutting tool.
(ii) The 3–7–7–1 network structure of SN_{TR} coated cutting tool.

Consequently, these two network structures will be considered with the next two factors to determine which network structure offers the best ANN model. In order to state the network structure that is labeled as the best ANN model, the first consideration factor is by referring to the last row of Table 12, predicted R_a value of ANN training. It was obtained that the minimum predicted R_a value in the testing phase for the 3–7–7–1 network structure of TiA1N coated and the 3–7–7–1 network structure of SN_{TR} coated are 0.135 and 0.097, respectively.

The second consideration factor is by referring to the last column of Table 13, MSE values of ANN training. It was obtained that the MSE value in the testing phase for the 3–7–7–1 network structure of TiA1N coated and the 3–7–7–1 network structure of SN_{TR} coated are 0.052 and 0.306, respectively.

With the two consideration factors above, it was found that the 3–7–7–1 network structure of TiA1N coated gave a smaller value in terms of the minimum predicted R_a; however the 3–7–7–1 network structure of SN_{TR} coated gave a smaller value in terms of the minimum MSE value. Therefore, to decide the best model, this study considers to the higher correlation value of the network structure. Since the 3–7–7–1 network structure of SN_{TR} coated has given a higher correlation value, it was selected to be the best ANN model.

The minimum normalized predicted R_a value of SN_{TR} coated that selected as the best ANN model is 0.097 (the fifth and sixth rows: axial data of Table 12). The normalized cutting condition values that lead to minimum predicted R_a value for SN_{TR} coated are: $v = 0.471$, $f = 0.100$, and $\gamma = 0.407$ (the fifth and sixth rows: axial data of Table 12). In terms of actual machining values, the cutting conditions values that lead to the minimum R_a using SN_{TR} coated are $v = 144.22$ m/min, $f = 0.025$ mm/tooth, and $\gamma = 9.5^\circ$ (the fifth and sixth rows: axial data of Table 4).

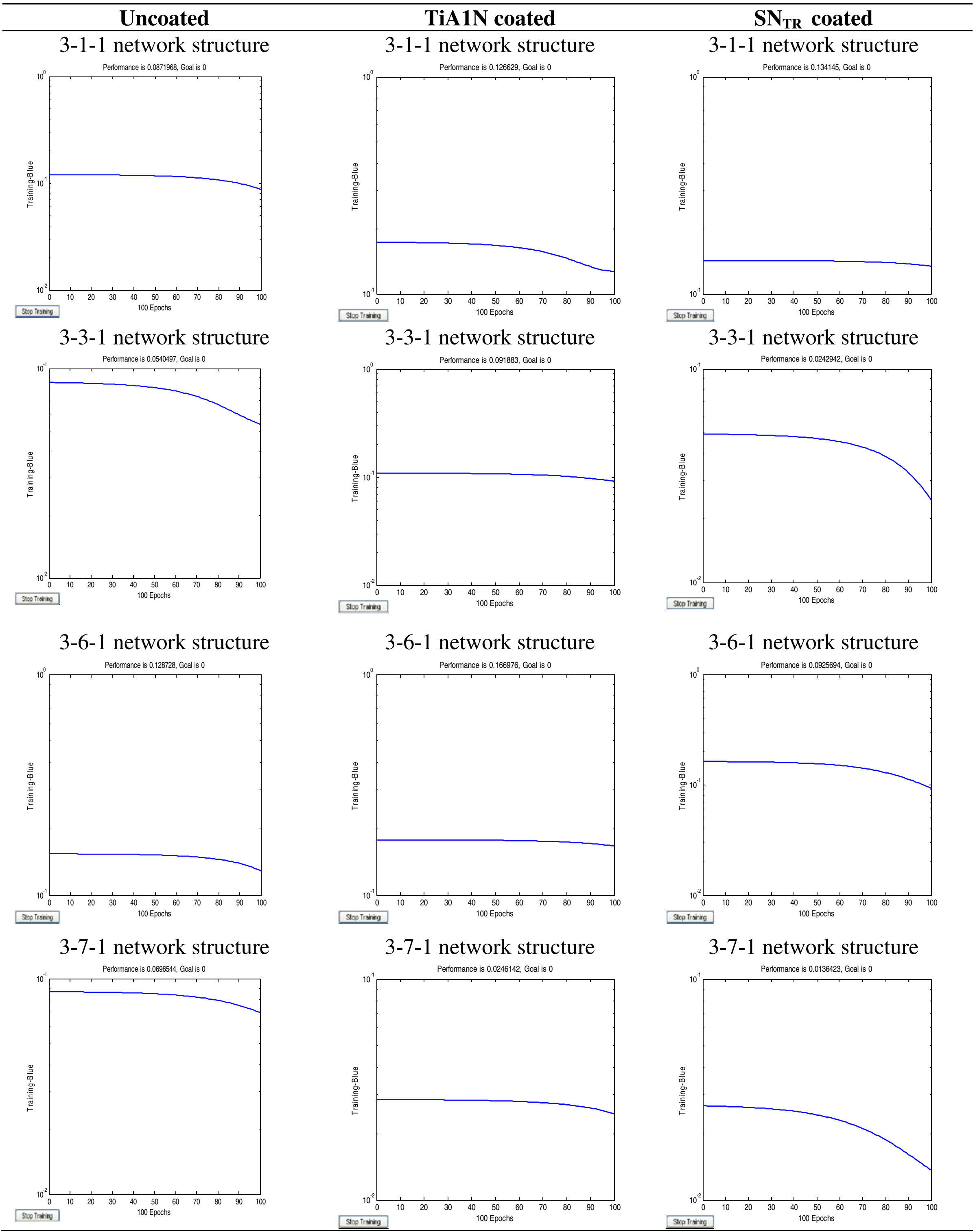

Fig. 6. MSE testing plot graph for ANN model with single hidden layer.

To estimate the actual value for the minimum R_a values, the normalization equation given in Eq. (11) is modified. Calculation for the expected actual value of R_a is given as follows:

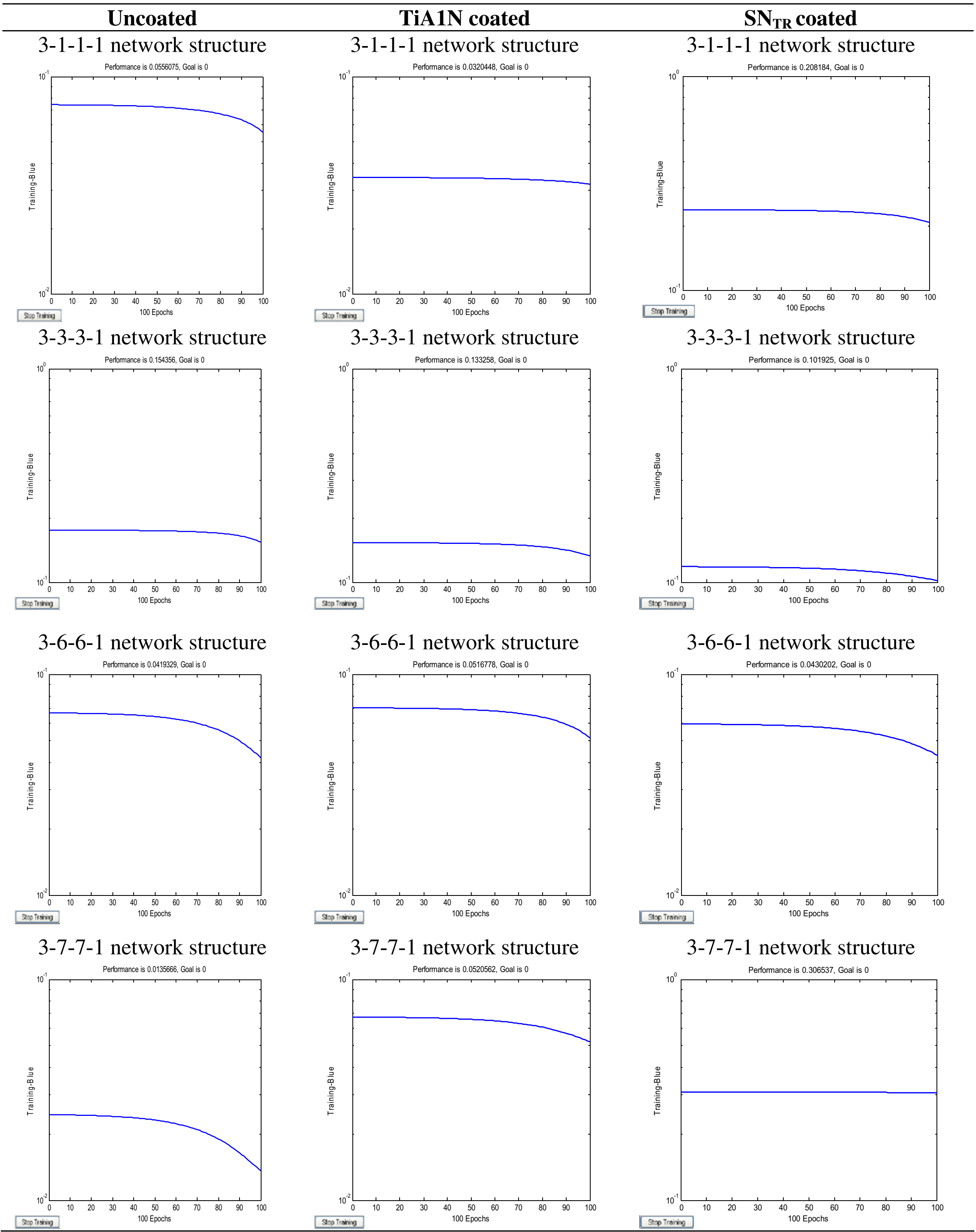

Fig. 7. MSE testing plot graph for ANN model with two hidden layers.

$$d_i = \frac{(y_{R_a} - 0.1)(d_{\max} - d_{\min})}{0.8} + d_{\min} = \frac{(0.097 - 0.1)(0.696 - 0.190)}{0.8} + 0.190 = 0.188103 \approx 0.188\ \mu\text{m} \tag{15}$$

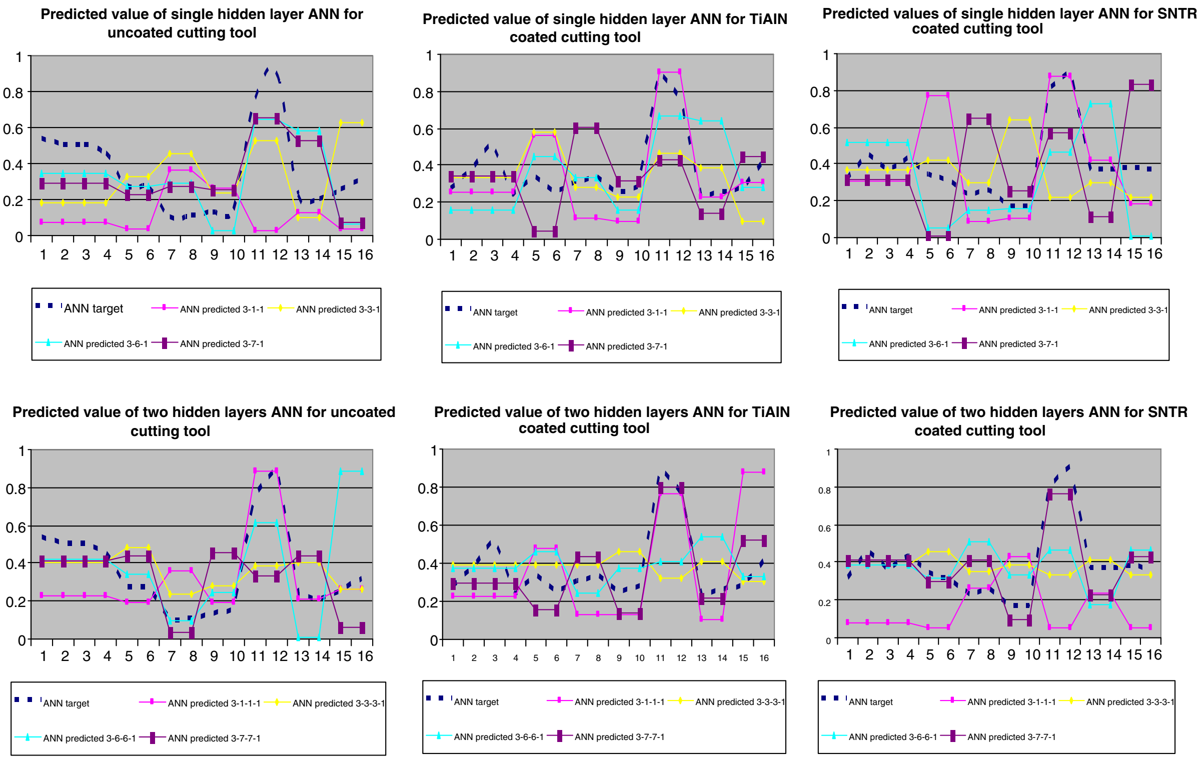

Fig. 8. ANN target vs. ANN output.

Table 14
Correlation values and similarity of the line pattern of ANN model.

Cutting tool	Pair of variables	Pattern line	Correlation value
Uncoated	Experimental-ANN 311	Less similar	–.652
	Experimental-ANN 331	Less similar	.158
	Experimental-ANN 361	Less similar	.593
	Experimental-ANN 371	Less similar	.555
	Experimental-ANN 3–1–1–1	Quite similar	.724
	Experimental-ANN 3–3–3–1	Less similar	.422
	Experimental-ANN 3–6–6–1	Less similar	.500
	Experimental-ANN 3–7–7–1	Quite similar	.232
TiA1N coated	Experimental-ANN 311	Quite similar	.780
	Experimental-ANN 331	Less similar	.275
	Experimental-ANN 361	Less similar	.442
	Experimental-ANN 371	Less similar	.304
	Experimental-ANN 3–1–1–1	Quite similar	.544
	Experimental-ANN 3–3–3–1	Less similar	–.543
	Experimental-ANN 3–6–6–1	Less similar	–.048
	Experimental-ANN 3–7–7–1	Quite similar	.804
SN_{TR} coated	Experimental-ANN 311	Quite similar	.728
	Experimental-ANN 331	Less similar	–.606
	Experimental-ANN 361	Less similar	.366
	Experimental-ANN 371	Less similar	.243
	Experimental-ANN 3–1–1–1	Less similar	–.592
	Experimental-ANN 3–3–3–1	Less similar	–.405
	Experimental-ANN 3–6–6–1	Less similar	.246
	Experimental-ANN 3–7–7–1	Quite similar	.869

Table 15
Statistics and correlations (experimental data vs. ANN training of 3–7–7–1 structure).

Variable	Mean	*N*	Std. deviation	Std. error mean	Correlation	Sig.
EXP_SN_{TR}	0.38950	16	0.20067	5.0168E–02	0.869	0.000
$ANN\_ SN_{TR}$	0.38150	16	0.18568	4.6420E–02		

Table 16
Paired samples test (experimental data vs. ANN training of 3–7–7–1 structure).

Pair	Paired differences					T	Df	Sig. (2-tailed)
	Mean	Std. deviation	Std. error mean	95% Conf. inter. of the difference				
				Lower	Upper			
EXP_SN_{TR} and ANN_ SN_{TR}	8.0000E−03	0.10006	2.5015E−02	−4.5317E−02	6.1317E−02	0.320	15	0.754

6. Validation and evaluation of results

It was observed in Table 8, the minimum predicted R_a value of the best regression model is 0.187 μm, given by SN_{TR} coated cutting tool. The process of validation for the regression model, basically, could refer to the paired-sample t test conducted in Section 4 in determining the best end milling model. According to the last row of Tables 9 and 10, it was proven that the mean R_a value reduced from experimental result to the SN_{TR} coated regression model result by 0.000667, $t(23) = 0.079$, $p = 0.938$. The 95% confidence interval ranges from −0.0168 to 0.0181 (including zero). Therefore, the two means, experimental and SN_{TR} coated regression model are not significantly different from each other.

The results of the paired-sample t test for SN_{TR} experimental data coupled with predicted value of the ANN 3–7–7–1 SN_{TR} coated (the best ANN model) training data are summarized in Tables 15 and 16 as follows.

According to Tables 15 and 16, it was proven that the mean R_a value reduced from SN_{TR} coated experimental result to the SN_{TR} coated ANN model result by 0.008, $t(15) = 0.320$, $p = 0.869$. The 95% confidence interval ranges from −0.04531 to 0.061317 (including zero). Therefore, the two means, SN_{TR} coated experimental and SN_{TR} coated ANN 3–7–7–1 model are not significantly different from each other. In other words, the average surface roughness predicted value of the ANN 3–7–7–1 SN_{TR} coated (the best ANN model) is similar to the average actual surface roughness found through experiment.

Consequently, focused on the predicted R_a value, the evaluation of the developed regression and ANN models are given as follows:

(a) Experimental data vs. regression.
As shown in Table 4, the minimum R_a value among all the cutting tools for experimental data is 0.190 μm, given by SN_{TR} cutting tool. Therefore, with $R_a = 0.187$ μm (Table 8), it can be stated that the regression model has given a lower minimum value of the R_a compared to experimental data by about 0.003 μm.

(b) Experimental data vs. ANN.
With $R_a = 0.188$ μm for ANN (Eq. (12)) and $R_a = 0.190$ μm for experimental data, it can be stated that ANN has given a lower minimum value of the predicted R_a by about 0.002 μm.

(c) Regression vs. ANN.
With $R_a = 0.187$ μm for regression, it can be stated that regression has given a lower minimum value of the R_a compared to ANN by about 0.001 μm.

7. Conclusion

This study has applied two techniques for estimating the minimum machining performance value. First technique, development of regression model, has been discussed in Section 4. Second technique, development of ANN model, has been discussed in Section 5.

According to the evaluation of the results discussed in Section 6, Table 17 summarizes results of the minimum machining performance values of experimental data, regression, and ANN. Consequently, Table 18 indicates the reduction percentage of the surface roughness that was given by the regression and ANN models when compared to the results of experimental data.

According to Table 17, it is clear that this study has found that both modeling approaches have outperformed the minimum R_a value of the experimental. From Table 18, it was found that both models have reduced the minimum R_a value of experimental data at about 1.57% and 1.05% respectively. Overall, it could be stated that the regression has given a better result when compared to ANN in predicting the minimum R_a value.

Table 17
Minimum value of surface roughness.

Approach	Minimum R_a (μm)
Experimental	0.190
Regression	0.187
ANN	0.188
GA [23]	0.1385
SA [24]	0.1385

Table 18
Reduction percentage of minimum surface roughness.

Approach		Reduction of R_a (%)
Modeling	Experimental vs. regression	1.57
	Experimental vs. ANN	1.05
Optimization	Experimental vs. GA	27
	Experimental vs. SA	27

Acknowledgments

Special appreciative to reviewer(s) for useful advices and comments. The authors greatly acknowledge the Research Management Centre, UTM and Ministry of Higher Education (MOHE) for financial support through the Exploratory Research Grant Vot. No. 4L003.

References

[1] J.T. Lin, D. Bhattacharyya, V. Kecman, Multiple regression and neural networks analyses in composites machining, Compos. Sci. Technol. 63 (2003) 539–548.
[2] N. Tosun, L. Ozler, A study of tool life in hot machining using artificial neural networks and regression analysis method, J. Mater. Process. Technol. 124 (2002) 99–104.
[3] K. Kanlayasiri, S. Boonmung, Effects of wire-EDM machining variables on surface roughness of newly developed DC 53 die steel: design of experiments and regression model, J. Mater. Process. Technol. 192–193 (2007) 459–464.
[4] U. Caydas, A. Hascalik, A study on surface roughness in abrasive waterjet machining process using artificial neural networks and regression analysis method, J. Mater. Process. Technol. 202 (2008) 574–582.
[5] I. Mukherjee, P.K. Ray, A review of optimization techniques in metal cutting processes, Comput. Ind. Eng. 50 (2006) 15–34.
[6] T. Ozel, Y. Karpat, Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks, Int. J. Mach. Tools Manuf. 45 (2005) 467–479.
[7] K.M. Rao, G. Rangajanardhaa, R.D. Hanumantha, R.M. Sreenivasa, Development of hybrid model and optimization of surface roughness in electric discharge machining using artificial neural networks and genetic algorithm, J. Mater. Process. Technol. 209 (2009) 1512–1520.
[8] H.C. Chen, J.C. Lin, Y.K. Yang, C.H. Tsai, Optimization of wire electrical discharge machining for pure tungsten using a neural network integrated simulated annealing approach, Expert Systems Appl. 37 (2010) 7147–7153.
[9] M. Nalbant, H. Gökkaya, I. Toktaş, G. Sur, The experimental investigation of the effects of uncoated, PVD- and CVD-coated cemented carbide inserts and cutting parameters on surface roughness in CNC turning and its prediction using artificial neural networks, Robot. Comput.-Int. Manuf. 25 (2009) 211–223.
[10] D. Karayel, Prediction and control of surface roughness in CNC lathe using artificial neural network, J. Mater. Process. Technol. 209 (2009) 3125–3137.
[11] N. Muthukrishnan, J.P. Davim, Optimization of machining parameters of Al/SiC-MMC with ANOVA and ANN analysis, J. Mater. Process. Technol. 209 (2009) 225–232.
[12] D. Venkatesan, K. Kannan, R. Saravanan, A genetic algorithm-based artificial neural network model for the optimization of machining processes, Neural Comput. Appl. 18 (2009) 135–140.
[13] H. Oktem, An integrated study of surface roughness for modelling and optimization of cutting parameters during end milling operation, Int. J. Adv. Manuf. Technol. 43 (2009) 852–861.
[14] M. Correa, C. Bileza, J. Pamies-Teixeira, Comparison of Bayesian networks and artificial neural networks for quality detection in machining process, Expert Systems Appl. 36 (2009) 7270–7279.
[15] E.S. Topal, The role of stepover ratio in prediction of surface roughness in flat end milling, Int. J. Mech. Sci. 51 (2009) 782–789.
[16] S. Aykut, M. Demetgul, I.N. Tansel, Selection of optimum cutting condition of cobalt-based superalloy with GONNS, Int. J. Adv. Manuf. Technol. 46 (2010) 957–967.
[17] P. Muñoz-Escalona, P.G. Maropoulos, Artificial neural network for surface roughness prediction when face milling Al 7075-T7351, J. Mater. Eng. Perform. 19 (2010) 185–193.
[18] A.M. Zain, H. Haron, S. Sharif, Prediction of surface roughness in the end milling machining using artificial neural network, Expert Systems Appl. 37 (2010) 1755–1768.
[19] Y.H. Tsai, J.C. Chen, S.J. Luu, An in-process surface recognition system based on neural networks in end milling cutting operations, Int. J. Mach. Tools Manuf. 39 (1999) 583–605.
[20] A.S. Mohruni, Performance Evaluation of Uncoated and Coated Carbide Tools When End Milling of Titanium Alloy Using Response Surface Methodology, Thesis Doctor of Philosophy, Universiti Teknologi Malaysia, Skudai, Johor, Malaysia, 2008.
[21] S.H. Yeo, M. Rahman, Y.S. Wong, Towards enhancement of machinability data by multiple regression, J. Mech. Work. Technol. 19 (1989) 85–99.
[22] C. Sanjay, C. Jyothi, A study of surface roughness in drilling using mathematical analysis and neural networks. Int. J. Adv. Manuf. Technol. 29 (2006) 846–852.
[23] A.M. Zain, H. Haron, S. Sharif, Application of GA to optimize cutting conditions for minimizing surface roughness in end milling machining process, Expert Systems Appl. 37 (2010) 4650–4659.
[24] A.M. Zain, H. Haron, S. Sharif, Simulated annealing to estimate the optimal cutting conditions for minimizing surface roughness in end milling Ti–6Al–4V, Mach. Sci. Technol. 14 (2010) 43–62.