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OPTIMIZATION OF SURFACE ROUGHNESS USING RSM AND ANN MODELLING ON THIN-WALLED MACHININGUNDER BIODEGRADABLE CUTTING FLUIDS

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ABSTRACT

Precise milling of thin-walled components is a difficult task process owing to the geometric complexity and low stiffness connected with them. This paper is concerned with a systematic comparative study between predicted and measured surface roughness. RSM and ANN applied in prediction and optimization of milling thin-walled steel components. Cutting speed, feed rate, radial and axial depth of cut are the main affecting process parameters on surface roughness. In order to protect our precious environment, this work utilized vegetable oil as biodegradable cutting fluids that resolve the lowest amount of ecological contamination provide well economic conditions. The milling have done under flood cooling and using uncoated carbide as cutting tool. The results indicate that the RSM and ANN models are very close to the experimental results, ANN predictions show better convergence than the RSM model. The best of surface roughness value (0.314 μm) can be achieved with a desirability of 98.6%, cutting speed, feed rate, radial and axial depth of cut were 125 m/min, 0.04 mm/tooth, 0.25 mm and 10 mm, respectively. The best configuration of the ANN structure was 4-16-1. The feed rate cause most significant effect on surface roughness, followed by axial and radial depth of cut.

Keywords: optimization, thin-walled, surface roughness, coconut oil, RSM, ANN.

INTRODUCTION

Thin-walled components are extensively used in aerospace industries, energy, automotive, military and shipbuilding industries. However, the structure of thin-walled parts usually complex and often unstable [1, 2]. In thin-walled machining, the thickness of the wall is diminished gradually, that makes it a complicated process [3]. This is because of the low rigidity of these parts because the largeness of surface area if compared to their thickness [4]. Therefore, thin-walled parts must be machined carefully.

Low rigidity of thin-wall parts will raise negative effect on the surface quality of work-piece [5]. Hence, surface quality is used to control the productivity of mechanical parts and as a quality indicator for the machined surface [6]. The quality of the machined surface also indicates work-piece material non-homogeneity. The parameters that evaluate the surface finish include feed, speed, and depth of cut, which the feed rate as the major parameter that influences surface roughness. Surface roughness measured in micrometre that is a group of irregular waves in the surfaces. The surface-finish has also effect on corrosion, heat transmission and wear resistance [7, 8]. Surface roughness frequently used as an indicator of a semi-finished product and also used for finished milling thin-walled C45 material. Cutting fluids are oftentimes applied in machining operations like milling which can improve the surface roughness. Recently, various kinds of cutting fluids are commercially prepared depending on final surface desired [6, 8, 9, 10].

The primary reason that the cost of cutting fluid enhance is that the cutting fluids need affluent treatments due to the poor bio-degradable before they get disposed [11]. Research on biodegradable cutting fluids generate to growing of ecological friendly cutting fluids in the market. Biodegradable substances are considerate to biochemical breakdown. The original molecule will disappear in the primary degradation and biomass, carbon dioxide and hydrogen will appear in the ultimate degradation [6]. While, ready biodegradability will degrade within the next 10 days, which the value of CO2 is 60% or O2 is 60% [12]. The growing request for biodegradable and non-toxic cutting fluid induce vegetable oils an alternative to mineral oils [10, 13].

One type of vegetable oil that has good oxidative stability is coconut oil. Coconut oil has observed in surface roughness research in turning AISI 304 steel and the result showed that coconut oil generated better machined surface compared soluble and straight cutting oils [8]. Coconut oil cause the smoothest surface compared with sesame oil, palm oil and olive oil during drilling AISI 316 stainless steel and coconut oil also produced better surface roughness in turning AISI 52100 steel [14].

Steels have already been chosen by a lot of previous researches as the work-piece. The machining of steel is sometimes challenging due to its unfavourable characteristic such as high hardening tendency, high ductility, low thermal conductivity and high modulus of elasticity [15]. Srikant and Rao in their work informed some of the research about steel machining among others machining AISI 1060 steel under MQL with a vegetable oil and the surface roughness research of AISI 304 steel under MQL using commercial vegetable oil. Oyarelemhi reported the turning of mild steel using palm kernel oil. Michalik *et al,* investigated thin-walled parts from steel C45 with a thickness 10 mm [16].

In order to optimized cutting condition for surface finish FEM usually applied. FEM simulation used

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in milling thin-wall steel XC45, thin-wall ST3S steel, 0.2% C plain carbon steel. FEM can be predicted the physical interaction with the work part surface, but it took approximately 100 hours. Therefore, this work the surface roughness optimization of milling thin-wall steel using response surface methodology (RSM) and artificial neural network (ANN) [4, 9, 17, 18].

Some surface roughness research about the use of RSM in machining such as in machining steel AISI 4340 SR, in machiningTi6Al4V under EDM process and in machining ceramic Al2O3 + TiC mixed ceramic, aluminium oxide-based ceramic, mild steel, medium carbon steel, AISI 1045 steel, pure tungsten, tungsten, En-8 carbon steel, Al/20%SiCp, alumina ceramic. Whereas ANN utilized in other surface roughness research like machining materials mild steel, hardened steel, pure tungsten, tungsten carbide-cobalt composite, Ti6Al4V, nickel based-alloy, silicon nitride [8, 20].

The purpose of this paper is to compare the utilized of Response Surface Methodology (RSM) and Artificial Neural Networks (ANN) in prediction and optimization surface roughness milling thin-wall steel using flood coconut oil. Debnath et al, informed that the most common type application method is flooding which flood cooling in machining aluminium alloy was the best in dimensional accuracy among dry and MQL. Cutting temperature, uneconomical surface finish and higher friction are the limitation of dry machining than that of in flood machining [11]. This work used uncoated carbide as machine tool. Lawal et al., informed in his review that uncoated carbide tool also used in the analysis of surface roughness in machining AISI 9310 mild steel by vegetable oil-based cutting fluid [21].

METHODOLOGY

Tool material, test workpiece and experimental setup

In this study, the thin-walled machining was performed on WEIDA XK 7132 vertical CNC milling machine as shown in Figure-1. It has a power capacity of 5.5 kW and a maximum spindle of 6000 rpm. The cutting tool used to be WC Co uncoated carbide end mill EMC 54100 - 4 flutes, 10 mm diameter and helical angle is 60^0. The thin-walled material is carbon steel for high temperature ASTM A106 with dimension is 3 x 20 x 100 mm. End milling of thin-walled under flood cooling use coconut oils as cutting fluids. The coconut oil has been considered as one of the cutting fluids for environmentally friendly machining. Specification of the coconut oil and experimental setup are shown in Table-1. The measurements were carried out by varying four parameters, namely cutting speed (V_c), feed rate (f_z), radial depth of cut (a_r) and axial depth of cut (a_x). Surface roughness of arithmetic (R_a) was considered as performance of machining.

Figure-1. CNC milling machine-WEIDA XK 7132.

Table-1. Specifications of coconut oil as cutting fluid.

Parameters (Unit)	Value
Density @ 15^0C (kg/m^3)	915.0
Absolute Viscosity @40^0C (cP)	1.840

Response Surface Methodology (RSM)

RSM is a statically technique to develop prediction empirical mathematical model and optimization from experimental data [22]. The mathematical model in this study can be expressed as Equation (1).

$$R_a = CV_c^k f_z^l a_r^m a_x^n \quad (1)$$

where, R_a is the surface roughness; V_c, f_z, a_r, a_x are the input variables; C, k, l, m, n are the constants of R_a. A logarithmic transformation is performed to convert Equations (1) into a linear model and expressed as indicated by Equation (2).

$$\ln R_a = \ln C + k \ln V_c + l \ln f_z + m \ln a_r + n \ln a_x \quad (2)$$

Or the equation linear form is described as Equation (3) follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 \quad (3)$$

where, y is the surface roughness in a logarithmic scale, x_1 to x_4 are input variables in the logarithmic transformation and β_0 to β_4 are the regression coefficients to be estimated. Equation (3) can be rewritten as Equation (4).

$$y_1 = y - \varepsilon = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4 \quad (4)$$

where, $\hat{y}_1$ is the response variable, y is the surface roughness in logarithmic scale, ε is the experimental errors, b_1 to b_4 are coefficients of the estimated value of β_0 to β_4. Equation (4) is the expression first order

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mathematical model and the quadratic model $\hat{y}_2$ can be extended as Equation (5) as follows:

$$y_2 = y - \varepsilon = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_{12}x_1x_2 + b_{13}x_1x_3 + b_{14}x_1x_4 + b_{23}x_2x_3 + b_{24}x_2x_4 + b_{34}x_3x_4 + b_{11}x_1^2 + b_{22}x_2^2 + b_{33}x_3^2 + b_{44}x_4^2 \quad (5)$$

The coefficients b_i and b_{ij} in first and second order models is obtained by the least square method. Statistic significant test needed for a calculation of the model equations. The steps of statistical significance are as follows: test the significance of the regression model, test the significance of the coefficients of individual model and test of the Lack of fit (LOF).

Artificial Neural Networks (ANN)

The ANN is a data processing system which has as a principle of biological neural system. It is one of artificial intelligence techniques to determine the input and output relationship, especially non-linear data. The structure configuration of ANN consists of several layers, namely input, hidden and output layer [23]. The diagram for a network with a single neuron in hidden layer is shown in Figure-2.

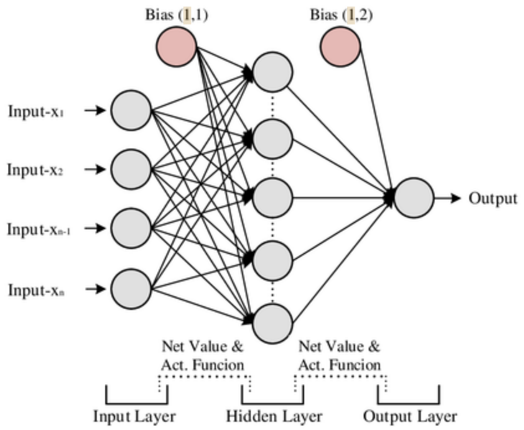

Figure-2. The ANN structure with three layers.

The data processing of input neurons to output neurons is performed by the means of training and testing. The output value of a neuron in the hidden layer and output layer is determined from the net value (n_v). This net value is then transferred by the activation function (A_f). The net value is calculated using the Equation (6).

$$n_v = f\left(\sum_{i=0}^{n} w_i x_i + \theta\right) \quad (6)$$

where, w_i is the weight in the interlayer, x_i is the input variables and θ is the bias.

In this study the tangent hyperbolic (tansig) activation function was used to activation function (A_f), as shown in Equation (7).

$$A_f = \frac{2}{1+e^{-n_v}} - 1 \quad (7)$$

The tansig activation function requires that the data input and target are in the range of +1 and -1, therefore all data must be normalized using Equation (8) as follows:

$$x_i = \frac{2}{(d_{max} - d_{min})}(d_i - d_{min}) - 1 \quad (8)$$

The evaluated network performance when the learning process (training and testing) is calculated by Equation (9).

$$x_i = \frac{2}{(d_{max} - d_{min})}(d_i - d_{min}) - 1 \quad (9)$$

where, MSE is the mean square error, N is the total experimental number, t_i and o_i are the target and output value.

Design of experimental

Relationship input variables and performance of machining were carried out based on the Central Composite Design (CCD). Component of CCD are factorial point of 2k (± 1), centre point (0) and axial point ((± 2), where k is the number of input variable. The distance between axial point and centre point is called radius rotatable (α), where α = (2k)^{¼} [22]. In the experiment, the input variables were coded by taking into account the capacity of CNC machine. The value of each level on the main points of the CCD is obtained from Equations (10) and listed in Table-2. The input variables in actual factor and the surface roughness are presented in Table-3 [24, 25].

$$x = \frac{\ln x_n - \ln x_{n0}}{\ln x_{n1} - \ln x_{n0}} \quad (10)$$

where, x is the level in coded form, x_n is the value of variable in n level, x_{n1} is the value of variable in n+1 level and x_{no} is the value of variable in centre level.

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Table-2. Input variables level and values at each level.

Input Variables		Levels				
		-2	**-1**	**0**	**+1**	**+2**
Cutting Speed	V_c(m/min)	64.00	80	100	125	156.25
Feed Rate	f_z (mm/tooth)	0.025	0.04	0.063	0.1	0.158
DOC Radial	a_r (mm)	0.200	0.25	0.32	0.4	0.51
DOC Axial	a_x (mm)	3.536	5	7.07	10	14.17

Table-3. Configuration of input variables, testing data and experiment results.

Run	Position Data	Input variables – Actual Factors				Surface Roughness (µm)
		V_c – m/min	f_z– mm/tooth	a_r - mm	a_x - mm	
1		80	0.04	0.25	5	0.350
2		125	0.04	0.25	5	0.283
3		80	0.10	0.25	5	1.150
4		125	0.10	0.25	5	1.063
5	Factorial Points	80	0.04	0.40	5	0.350
6		125	0.04	0.40	5	0.340
7		80	0.10	0.40	5	0.950
8		125	0.10	0.40	5	0.527
9		80	0.04	0.25	10	0.380
10		125	0.04	0.25	10	0.313
11		80	0.10	0.25	10	1.357
12		125	0.10	0.25	10	1.213
13		80	0.04	0.40	10	0.627
14		125	0.04	0.40	10	0.357
15		80	0.10	0.40	10	1.337
16		125	0.10	0.40	10	0.850
17	Axial Points	64	0.063	0.32	7.07	0.750
18		156.25	0.063	0.32	7.07	0.460
19		100	0.025	0.32	7.07	0.440
20		100	0.158	0.32	7.07	2.477
21		100	0.063	0.20	7.07	0.477
22		100	0.063	0.51	7.07	0.583
23		100	0.063	0.32	3.54	0.473
24		100	0.063	0.32	14.14	0.487
25	Center Points	100	0.063	0.32	7.07	0.473
26		100	0.063	0.32	7.07	0.413
27		100	0.063	0.32	7.07	0.467
28		100	0.063	0.32	7.07	0.480
29		100	0.063	0.32	7.07	0.533
30		100	0.063	0.32	7.07	0.523
1	Testing Data	100	0.040	0.40	10	0.453
2		125	0.063	0.40	10	0.478
3		80	0.100	0.40	7.07	1.090
4		100	0.063	0.32	7.07	0.520

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RESULT AND DISCUSSIONS

Surface Roughness Prediction by RSM

In the RSM modelling, the effect of input variables on surface roughness is determined by Analysis of Variance (ANOVA). The ANOVA is performs with a confidence level of 95% or a significance level α = 5%. The prediction model using 30 experimental data was CCD data at the factorial, axial and center points. The prediction model of first order in coded factor is given in Equation (11).

$$y_1 = -0.5137 - 0.1257x_1 + 0.4838x_2 - 0.0011x_3 + 0.0727x_4 \quad (11)$$

By substituting the Equation (10) into the Equation (11) to obtain the empirical equation of surface roughness is shown in Equation (12).

$$R_a = 95.545V_c^{-0.563} f_z^{1.047} a_r^{-0.005} a_x^{0.210} \quad (12)$$

The ANOVA was performed to check the model of adequacy. Table-4 illustrated the ANOVA result of the first order model. It is obvious that the Model F-Value (42.44) in Model and Fit F-Value (5.86) in Lack of Fit were significant. Therefore, the first order cannot be used to modelling surface roughness and needs further analysis on the model using the second order. And to prove the model of adequacy on the second order, the ANOVA result is Table-5.

Table-4. ANOVA to predict surface roughness in first-order model.

Source	Sum of Squares	df	Mean Square	F-Value	P-value Prob>F	Remarks
Model	6.95	4	1.74	42.44	< 0.0001	significant
A-Vc	0.3912	1	0.3912	9.55	0.0049	
B-fz	6.42	1	6.42	156.83	< 0.0001	
C-DOCrad	0.0000	1	0.0000	0.0007	0.9788	
D-DOCax	0.1368	1	1368	3.34	0.0796	
Residual	1.02	25	0.0410			
Lack of Fit	0.9822	20	0.0491	5.86	0.0295	significant
Pure Error	0.0419	5	0.0084			
Cor Total	7.98	29				

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Table-5. ANOVA to predict surface roughness in second order model.

Source	Sum of Squares	df	Mean Square	F-Value	P-value Prob>F	Remarks
Model	7.57	14	0.5405	19.71	< 0.0001	significant
A-Vc	0.4781	1	0.4781	17.43	0.0008	
B-fz	4.21	1	4.21	153.43	< 0.0001	
C-DOCrad	0.0054	1	0.0054	0.1974	0.6632	
D-DOCax	0.2038	1	0.2038	7.43	0.0156	
AB	0.0008	1	0.0008	0.0295	0.8660	
AC	0.0692	1	0.0692	2.52	0.1330	
AD	0.0078	1	0.0078	0.2839	0.6020	
BC	0.2715	1	0.2715	9.90	0.0067	
BD	0.0179	1	0.0179	0.6531	0.4316	
CD	0.0584	1	0.0584	2.13	0.1650	
A^2	0.0720	1	0.0720	2.63	0.1259	
B^2	0.0304	1	0.0304	1.11	0.3088	
C^2	0.0066	1	0.0066	0.2394	0.6317	
D^2	0.0421	1	0.0421	1.54	0.2342	
Residual	0.4114	15	0.0274			
Lack of Fit	0.3695	10	0.0370	4.41	0.0576	not significant
Pure Error	0.0419	5	0.0084			
Cor Total	7.98	29				

The model F-value of 19.17 indicated that the model was significant and the Lack of Fit (LOF) value of 5.86 that it was not significant. Accordingly, the second order model was chosen to develop prediction and optimization model. The Equation (13) is the second order model in terms of the actual factors as below:

$$\begin{aligned} R_a = & -2.061 - 0.01V_c + 27.859f_z \\ & + 3.768a_r + 0.025a_x - 0.01V_c f_z \\ & - 0.039V_c a_r - 0003V_c a_x - 57.442 f_z a_r \qquad (13) \\ & + 0.442 f_z a_x + 0.32a_r a_x + 0.0001V_c^2 \\ & + 28.285 f_z^2 + 2.496a_r^2 - 0.005a_x^2 \end{aligned}$$

The tendency to influence machining conditions on surface roughness can be explained from the Equation (13) and the perturbation plot of the Figure-3. Machining conditions which significantly affect the increase in surface roughness are feed rate, axial and radial depth of cut, respectively. The feed rate has the more significant effect than radial and axial depth of cut. The contrary phenomenon shows that surface roughness are smoother by increasing cutting speed. Therefore, to obtain a smooth surface finish in machining, it is done with a combination of high cutting speed and small feed rate and depth of cut.

Optimum machining conditions using the function desirability and minimize the response to determine the best parameters, the results are shown in Table-6.

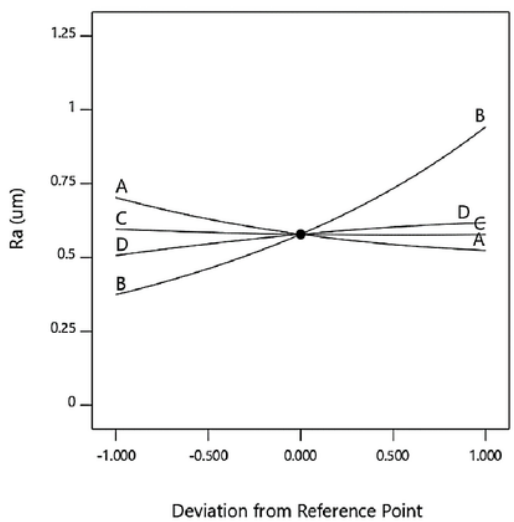

Figure-3. The perturbation plot for surface roughness.

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The optimum result are the cutting speed of 125 m/min, the feed rate of 0.04 mm/tooth, radial depth of cut of 0.25 mm and axial depth of cut of 10 mm. Minimum surface roughness value (0.314 μm) could be achieved with optimized machining condition with 98.6% desirability.

Table-6. Optimum machining condition for surface roughness.

Number	V_c	f_z	DOC Radial	DOC Axial	Ra	Desirability	
1	**1125.000**	**0.04**	**0.250**	**10.000**	**0.314**	**0.986**	**Selected**
2	1124.691	0.04	0.250	10.000	0.315	0.986	
3	1120.384	0.04	0.250	9.994	0.315	0.985	
4	1125.000	0.04	0.358	5.000	0.315	0.985	
...	...	...	...	...	...	...	

Surface Roughness Prediction by ANN

In the analysis by ANN, the network was trained with the same data with RSM analysis and data for testing is data 31 to the data 34 in Table-3. The Matlab with the neural network code was utilized for training and testing. The learning process were based Feed-forward back propagation method (BP) and training function using Levenberg-Marquardt (LM) algorithm. The Levenberg-Marquardt optimization is often the fastest algorithm of all back propagation training functions. It is highly recommended as a first option algorithm, although LM function requires less memory than other algorithms [26, 27, 28, 29].

In this study, the ANN network configuration was 4-n-1, where n is the number of neurons in the hidden layer, such as shown in Figure-1. There are no rules about the number of neurons in hidden layers, and it depends on the complexity and specifications of the data. Many researchers use only one hidden layer to obtain optimal conditions [25, 30].

Network functions and learning data in the training and testing process are summarized as follows: transfer function is tansig, training function is tranlm, the performance goal value was 1e-5, the number of epochs/training was 1000 and the maximum number of epochs was 30.000, and other values are carried out with the default value of the LM algorithm.

The optimum number of neurons in the hidden layer is determined based on the MSE after training and testing. The results of training and testing to obtain the best network performance for the number of neurons 1 to 20 are shown in Figure-4.

It can be seen that the results of ANN models (training and testing) are almost all better than RSM based models. The best number of neurons in the hidden layer was 16 neurons or neural network structure with 4-16-1 configuration.

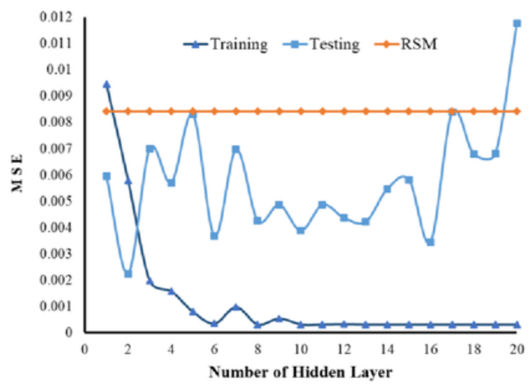

Figure-4. The network performances in hidden layers.

The experimental data and the results predicted by the RSM and ANN analysis are presented in Table-7 and Figure-5. Percentage range error between the experimental results and predictions RSM was 1.06% to 31.99%. On the other hand, percentage range error between the experimental results and predictions ANN was 4.E-08% to 16.5%. However, the average percentage of total errors obtained from all prediction data were 8.817% (prediction) and 3.64% (validation) for RSM models. On the ANN model the average percentage of total errors was 1.315% (training) and 3.57% (testing). This means that the values of the RSM and ANN models are very close to the experimental results. And, both training and testing, it was revealed that ANN predictions have shown convergence that is better than RSM predictions. This was also the result of the same analysis by other researchers [25, 31].

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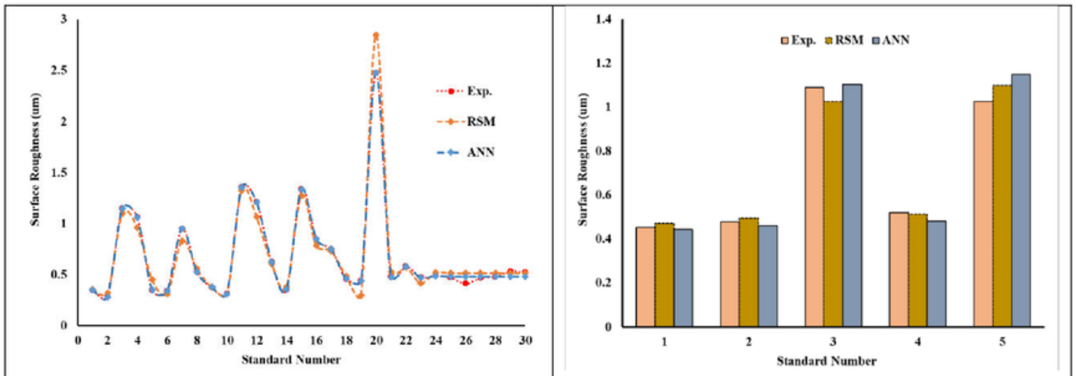
Table-7. The surface roughness values of the experimental results and predictions by RSM and ANN.

Run	Surface Roughness (μm)			Percentage Error	
	Experiment	Predicted by		RSM	ANN
		RSM	ANN		
Experimental results, prediction by RSM and training by ANN					
1	0.350	0.355	0.350	1.453	2.E-04
2	0.283	0.320	0.283	13.056	4.E-02
3	1.150	1.099	1.150	4.417	5.E-07
4	1.063	0.963	1.063	9.416	6.E-06
5	0.350	0.451	0.350	28.715	4.E-06
6	0.340	0.312	0.340	8.173	2.E-05
7	0.950	0.832	0.950	12.461	5.E-07
8	0.527	0.560	0.527	6.323	5.E-07
9	0.380	0.375	0.380	1.258	1.E-04
10	0.313	0.310	0.313	1.059	1.E-04
11	1.357	1.326	1.357	2.265	5.E-07
12	1.213	1.064	1.213	12.266	2.E-05
13	0.627	0.606	0.627	3.420	1.E-06
14	0.357	0.384	0.357	7.679	2.E-07
15	1.337	1.276	1.337	4.534	8.E-08
16	0.850	0.788	0.850	7.324	4.E-08
17	0.750	0.733	0.750	2.242	2.E-06
18	0.460	0.485	0.460	5.332	9.E-05
19	0.440	0.299	0.440	31.996	2.E-04
20	2.477	2.848	2.477	14.959	3.E-05
21	0.477	0.527	0.477	10.458	9.E-08
22	0.583	0.573	0.583	1.718	3.E-07
23	0.473	0.419	0.473	11.509	8.E-04
24	0.487	0.520	0.487	6.693	3.E-04
25	0.473	0.514	0.482	8.760	2.E+00
26	0.413	0.514	0.482	24.561	2.E+01
27	0.467	0.514	0.482	10.158	3.E+00
28	0.480	0.514	0.482	7.174	3.E-01
29	0.533	0.514	0.482	3.483	1.E+01
30	0.523	0.514	0.482	1.637	8.E+00
Average				**8.817**	**1.315**
Experimental results, prediction by RSM and testing by ANN					
1	0.453	0.472	0.443	4.16	2.13
2	0.478	0.494	0.461	3.36	3.59
3	1.090	1.026	1.103	5.88	1.16
4	0.520	0.514	0.482	1.15	7.40
Average				**3.64**	**3.57**



(Prediction data)	(Validation data)

Figure-5. The actual plot of experimental and predictive surface roughness by RSM and ANN.

CONCLUSIONS

The surface roughness optimization in end milling thin-walled work-piece using RSM and ANN models has been developed. The second order type uses the RSM model and for training the network in ANN with the Levenberg-Marquardt algorithm. The prediction results of both methods reveal the percentage of the average error is 8.817% (prediction) and 3.64% (validation) in the RSM model, furthermore 1.315% (training) and 3.57% (testing) in the ANN model. It means that the values of the RSM and ANN models were very close to the experimental results, and predictions of ANN showed better convergence than expected RSM.

In the analysis of RSM, the best of surface roughness value (0.314 µm) can be achieved with optimized machining condition with desirability of 98.6%. The optimal conditions of cutting speed, feed rate, radial and axial depth of cut were 125 m/min, 0.04 mm/tooth, 0.25 mm and 10 mm, respectively. In the analysis of ANN, the best network structure configuration was 4-16-1.

From the development of the model shows that the feed rate cause most significant effect on surface roughness, followed by axial DOC and radial DOC. On the contrary, surface roughness is smoother with increased cutting speed.

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