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Application of RSM and ANN in Predicting Surface Roughness for Side Milling Process under Environmentally Friendly Cutting Fluid

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Abstract. The paper presents a potential study on prediction of surface roughness in side milling by optimization techniques approaches. Two methods, response surface methodology (RSM) and artificial neural networks (ANN) were used for optimized prediction. The model of surface roughness was expressed as the main parameter in side milling term of cutting speed, feed rate and axial depth of cut. Rotatable central composite design (RCCD) is employed in developing second-order response surface mathematical model. The ANN model using a multi-layer feed forward, back propagation and training function Levenberg-Marquardt (LM) algorithm with a single hidden layer. Vegetable oils have often been recommended as sustainable alternative cutting fluid since the ecological and health impacts in the use of mineral oil have been questioned and also the rising cost of mineral oil. The advantages of oxidative stability of coconut oil as vegetable oil were utilized in this study to investigate surface roughness of low carbon steel. The machining of ferrous alloy like steel is sometimes a difficult task. This study used uncoated tool because it is suitable when turning and milling alloy. Flood condition was selected because it has been proved effective at low cutting speed. The analysis predicted by RSM and ANN models resulted a good agreement between the experimental and predicted values. The results indicated that the ANN model predict with more accurate compared with the RSM model.

Keywords: RSM, ANN, Roughness, Side milling, Cutting fluid

1. Introduction

In the past few years, many scientific studies have predicted surface roughness in end milling by mathematical model approaches. One of the most common metal removal operations used in the industry is the end milling process which can easily machine complicated workpiece [1]. Metal removal is important in the manufacturing industries provides the required surface finish [2]. Surface roughness always used as a quality indicator of product [3]. One machining method of the end milling operation widely used for mould, die, monolithic parts and machine components, is side milling [1][4]. Studies about side milling have been done such as analyst surface roughness in side milling of AISI D2 steel [5] and surface roughness were also analyzed in side milling of S45C steel. The important machining parameter of side milling affecting surface roughness includes cutting speed, feed rate and axial depth of cut [1]. Even small changes in any of these parameters may have a significant effect on the surface roughness. It is expected that the predictive modelling and optimization will provide a cheaper and time efficient experimental research [6].

RSM is a statistical procedure and mathematical modelling was used for developing, improving and optimizing between independent variables and dependent variables. The relationship between independent variables and dependent variables are expressed by a first order or second order polynomial [7]. An ANN is a model for predicting response parameters (dependent variable) using the same principles as biological neural systems. It's one of the most proper analysis in artificial intelligence (AI). The ANN can be effectively used to determine the input-output relationship of a complex process and is considered as a tool in nonlinear statistical data modelling. RSM and ANN applications are used to predict and optimize arithmetic mean deviation surface roughness (Ra). Both of the methods are the most commonly to optimize by many researchers [8] [9] [10] [11].

Scientific studies have been done in optimizing predicted cutting parameter through RSM and ANN approach. The surface roughness studies using ANN such as in turning of AISI H13 steel [12], milling of ductile iron grade 80-55-06 [13], turning of Ti6Al4V [14] and in milling AISI 1060 steel [9]. While studies that compared both method RSM and ANN in optimizing surface roughness such as in milling of ductile iron grade 80-55-06 [13], turning of AISI 1040 steel [15], turning of aluminum alloy 6061 [16] and in milling of Ti6242S [10].

Mineral oil as petroleum cutting fluid are limited resources. Availability and numerous benefits of vegetable oil have made them economical to use. Vegetable oils renewability and less costly than synthetic base stock. Petroleum-based cutting fluid also have a negative effect on the environment such as groundwater and surface water contamination, air pollution, soil contamination, agricultural production and food contamination because of its poor biodegradability. Mineral oil used to be containing some additives which harmful and toxic [17] [18]. Mineral-based cutting fluid hazardous on storage and disposal which two-thirds of consuming cutting fluid needs to be disposed. Due to the widespread use of mineral-based cutting fluid, they cause significant environmental pollution throughout their life cycle while vegetable oil remains biodegradable with low toxicity at all stages of its life. The carbon cycle of a mineral oil-based product is open, this leads carbon dioxide increase in the atmosphere and contribute to global warming. Vegetable oil reduced the ecological problems. Vegetable oils have a higher flash point, hence do not tend to generate mist and fire hazard. Comparing to the rate 0f 2 % for the overall lubricant market, environmentally favorable lubricants are expecting an annual growth rate of 7–10 % [3] [17] [18] [19] [20].

Vegetable oils have oftentimes been recommended as sustainable alternative cutting fluid include in terms of surface roughness for softer metals and alloys. Analysis of surface roughness with the use of vegetable oil such as using of castor oil, sunflower oil and soybean-base fluid, palm oil [2] [20] [21] [22]. Other research has done and recorded about vegetable oil as cutting fluid in machining such as the use of rapeseed oil, commercial vegetable oil (Coolube 2210)) and canola oil, refined canola, palm oil, olive oil, jatropha oil, linseed oil and castor oil. The research has been reported that lower viscosity of vegetable oil possesses better fluidity and faster cooling capacity, therefore vegetable oil with lower viscosity recommended during machining carbon steel [2][17][18][20][22][23][24].

Coconut oil has the viscosity relatively lower than other vegetable oil, hence coconut oil was selected to milling low carbon steel in this study. Other advantages of coconut oil since it has saturated fatty acid more than 85% with the result that oxidative stability better than others vegetable oil [24]. The oxygen bond in vegetable oil can lead to metal oxidation and weaken the metal [19]. This could explain that coconut oil could decreased cutting tool temperature by 7% compared to sesame oil in machining AISI 1040 steel, coconut oil gave the smoothest surface compared with palm oil, olive oil and sesame oil in drilling AISI 316 stainless steel and coconut oil produced lesser surface roughness in turning AISI 52100 steel [20]. Paper review [18] informed coconut oil, groundnut oil and palm kernel oil were used during turning mild steel, copper and aluminum to analysis cutting force. While [3] also informed in their review that coconut oil improved surface finish AISI 304 better than soluble oil and coconut oil also performed better in surface roughness than SAE-40 based lubricant during turning AISI 1040. Because of the advantage of coconut oil therefore this paper use coconut oil to investigate surface roughness.

This paper reported the machining of low carbon steel in flood coconut oil. The machining of ferrous alloy like steel is sometimes a difficult task because of high strength, low thermal conductivity, high ductility and high work hardening tendency Flood condition was selected because it is proven that flood cooling very effective at lower cutting speed [22].

Uncoated tool was used in this study. Most studies have concluded that uncoated tool remains the best tool when turning and milling alloy [25]. A series of surface roughness experiments used uncoated carbide in milling Ti6Al4V have informed in the review [22]. Uncoated carbide tool was used during turning Ti6Al4V using rapeseed oil [21]. Uncoated carbide tool was also used in the he analysis of surface roughness on turning AISI 9310 mild steel by vegetable oil-based cutting fluid [2].

2. Methodology

The workpiece material in this study was Carbon Steel SS400. This material is widely used as general construction and machine components. Chemical properties of SS400 are given in table 1. The set up employed a conventional vertical milling machine using uncoated carbide end mill EMC54100-4 flute with 10 mm diameter. The side milling experiments used coconut oil as the cutting fluids, and mineral oil was also used as comparison. Cutting speed (V_c), feed per tooth (f_z) and axial depth of cut (a_x) were machining parameters as input variables. The output variable was surface roughness, and it was analyzed using RSM and ANN. The surface roughness value was measured using a roughness tester Accretech Handysurf E- 35A/E with evaluation length 12.5 mm, cut off 2.5 mm and speed 0.6 mm/s.

Table 1. Chemical composition of workpiece material (average %)

C	Si	Mn	Cr	Mo	Ni	Fe
0.217	0.561	0.318	0.113	0.242	0.0386	98.5

The relationship between machining parameters and surface roughness are conducted based on the Rotatable Central Composite Design (RCCD). Cutting speed, feed per tooth and axial depth of cut were machining parameters. The RCCD contains embedded 2k factorial points (±1), where k is the number of input parameters, center points (0) and axial points (±2). The distance between the center and axial point, α = 1.682 [7]. The level and coding of the machining parameters used in this study are shown in table 2. Machining parameter values adjusted to the capability of milling machine used. For all experiments the value of radial depth of cut (a_r) was 0.5 mm.

Table 2. Machining parameters and the value of each level

Levels	**Level (Coded)**				
	Lowest	**Low**	**Centre**	**High**	**Highest**
Coding	-2	-1	0	1	2
Cutting speed (Vc), m/min	2.67	8.33	22.72	31.11	40.86
Feed rate, (fz), mm/tooth	0.033	0.05	0.075	0.10	0.117
Ax. depth of cut, (a_{ax}), mm	3.63	5.0	7.0	9.0	10.36

3. Result and discussions

The variations of machining parameters (in actual coded) and experimental results are given in table 3. To estimate the surface roughness value based on RSM using Design Expert 10.0 software, and Matlab R14a software was used for ANN prediction. From figure 1, it could be seen that surface roughness resulted by machining using vegetable oil is on average 16.71% better than mineral oil. Long polar fatty acid chains of triglyceride structure in vegetable oil provide high strength lubricant film that interact strongly with a metallic surface, reducing wear and friction [18]. The wear scars produced by vegetable oil are slightly lower than those produced by mineral oil [19].

Table 3. Machining parameters and experimental results

Exp. No.	V_c **m/min**	f_z **mm/tooth**	a_x **mm**	**Surface Roughness - µm**	
				Mineral Oil	**Coconut Oil**
1	8.33	0.05	5.0	3.281	2.531
2	31.11	0.05	5.0	2.973	2.363
3	8.33	0.10	5.0	3.654	2.794
4	31.11	0.10	5.0	3.361	2.661

Exp. No.	V_c m/min	f_z mm/tooth	a_x mm	Surface Roughness - μm	
				Mineral Oil	Coconut Oil
5	8.33	0.05	9.0	2.52	1.770
6	31.11	0.05	9.0	3.037	2.287
7	8.33	0.10	9.0	5.07	4.520
8	31.11	0.10	9.0	3.562	3.112
9	2.67	0.075	7.0	3.325	2.625
10	40.86	0.075	7.0	3.192	2.592
11	22.47	0.033	7.0	2.325	2.225
12	22.47	0.117	7.0	4.94	4.690
13	22.47	0.075	3.63	2.433	2.063
14	22.47	0.075	10.36	3.072	2.642
15	22.47	0.075	7.0	3.135	2.635
16	22.47	0.075	7.0	3.29	2.99
17	22.47	0.075	7.0	2.971	2.571
18	22.47	0.075	7.0	3.315	2.715

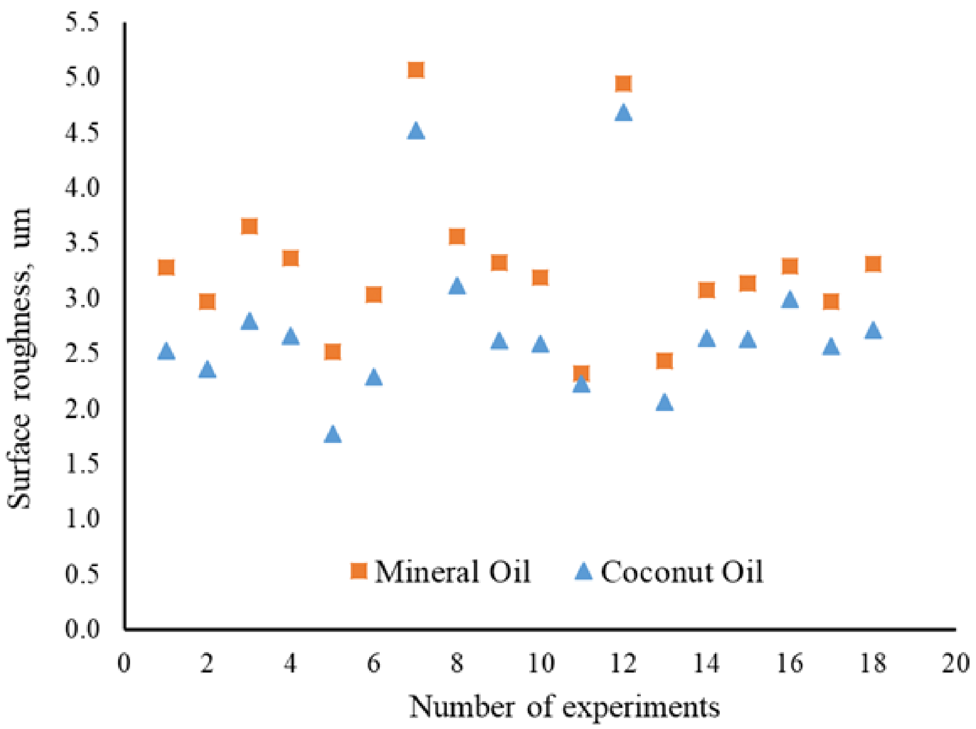


Figure 1. Chart number of experiment vs Ra for mineral oil and coconut oil

3.1. Prediction Model by RSM

In this study the second order model was used in developmentally and prediction non-linear curve. The second order polynomial equation to predict the surface roughness as shown in equation (1) [7].

$$y = \beta_0 + \sum_{j=1}^{k} \beta_j X_j + \sum_{j=1}^{k} \beta_{jj} X_j^2 + \sum_{i}^{k-1} \sum_{j=1}^{k} \beta_{ij} X_i X_j + e \quad (1)$$

where, y is variable of response; β_0, β_1, ... β_k, are unknown regression parameters; X_i and X_j are independent variables; e is the error term. Analysis of Varian (ANOVA) is used to analysis the effect of each parameter of Surface roughness. Analysis was set a significance level as 5% and confidence level as 95%. The adequacy and fitness of the model for second order are shown in table 4.

Table 4. ANOVA for surface roughness (a) mineral oil and (b) coconut oil

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	7.50	9	0.8335	5.53	0.0123	significant
A-Vc	0.3237	1	0.3237	2.15	0.1810	
B-Fz	5.24	1	5.24	34.74	0.0004	
C-a	0.3019	1	0.3019	2.00	0.1948	
AB	0.3829	1	0.3829	2.54	0.1497	
AC	0.0133	1	0.0133	0.0884	0.7738	
BC	0.6693	1	0.6693	4.44	0.0682	
A²	0.0777	1	0.0777	0.5153	0.4933	
B²	0.5225	1	0.5225	3.47	0.0997	
C²	0.1470	1	0.1470	0.9751	0.3523	
Residual	1.21	8	0.1508			
Lack of Fit	1.13	5	0.2260	8.92	0.0507	not significant
Pure Error	0.0760	3	0.0253			
Cor Total	8.71	17				

(a)

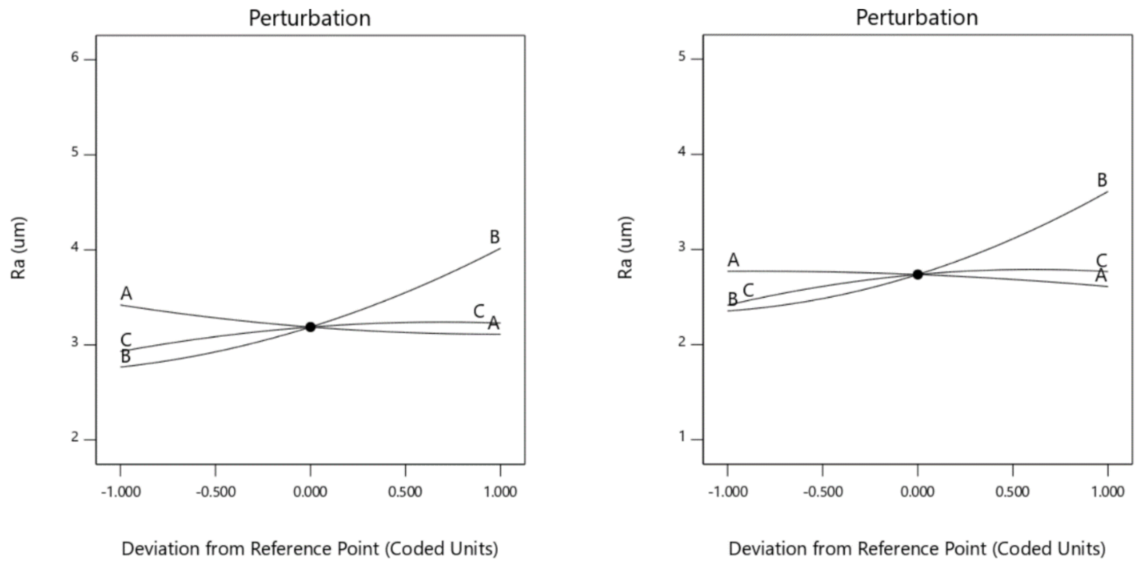
Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	8.38	9	0.9313	8.03	0.0037	significant
A-Vc	0.0875	1	0.0875	0.7542	0.4104	
B-Fz	5.29	1	5.29	45.58	0.0001	
C-a	0.4174	1	0.4174	3.60	0.0944	
AB	0.3598	1	0.3598	3.10	0.1162	
AC	0.0421	1	0.0421	0.3626	0.5637	
BC	1.14	1	1.14	9.79	0.0140	
A²	0.0270	1	0.0270	0.2328	0.6424	
B²	0.7560	1	0.7560	6.52	0.0340	
C²	0.2690	1	0.2690	2.32	0.1662	
Residual	0.9278	8	0.1160			
Lack of Fit	0.8257	5	0.1651	4.85	0.1119	not significant
Pure Error	0.1021	3	0.0340			
Cor Total	9.31	17				

(b)

From table 4, analysis of variance the model F-values are 5.53 and 8.03 implied that the model was significant. There were only 0.37% and 1.2% chance that the model's value this large could occur due to noise. The LoF are 8.92 and 4.85 implied that it was not significant, and there were 5.07% and 11.19% chance that model f values could due to noise. The equation in term of code factors as is shown equation (2) (mineral oil) and equation (3) (coconut oil), where x_1, x_2 and x_3 are cutting speed, feed rate and axial depth of cut, respectively. Figure 2 shows the perturbation plot for three machining parameters.

$$R_a = 3.188 - 0.154x_1 + 0.625x_2 + 0.150x_3 - 0.216x_1x_2 - 0.040x_1x_3 + 0.290x_2x_3 + 0.078x_1^2 + 0.204x_2^2 - 0.108x_3^2 \quad (2)$$

$$R_a = 2.737 - 0.080x_1 + 0.678x_2 + 0.176x_3 - 0.210x_1x_2 - 0.072x_1x_3 + 0.377x_2x_3 - 0.046x_1^2 + 0.245x_2^2 - 0.146x_3^2 \quad (3)$$



(a) (b)

Figure 2. Plot of perturbation for surface roughness, (a) mineral oil and (b) coconut oil

The second order model and perturbation plot showed that with the feed rate and axial depth of cut increases, surface roughness increased. However, feed rate has the most significant effect than axial depth of cut. The opposite trend for cutting speed, the increase of cutting speed resulted in the decrease of surface roughness. Hence, a variety of high cutting speed with low feed rate and axial depth of cut are required to produce a smooth surface finish in machining.

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The aim of optimization, was to find the best parameters that minimize the response. Table 5, present a possible solution for optimum machining parameters in side milling SS400 using uncoated carbide. Surface roughness with the criteria of minimum range, the results showed that the cutting speed is 31.11 m/min, the feed rate is 0.05 mm/tooth and axial depth of cut 5.0 mm with surface roughness value of 2.98 µm for mineral oil and 2.565 µm for coconut oil.

Table 5. Optimum machining parameters

Number	Cutting Speed	Feed Rate	Axial Depth of Cut	Surface Roughness	Desirability		Note
1	**31.110**	**0.050**	**5.000**	**2.980**	**0.934**	**Selected**	Mineral oil
2	31.110	0.050	5.000	2.978	0.933		
1	**31.110**	**0.050**	**5.000**	**2.565**	**1.000**	**Selected**	Coconut oil
2	31.110	0.050	5.000	2.565	1.000		

3.2. Prediction Model by ANN

The ANN structure is built with several neurons on input layer, hidden layer and output layer. The hidden layers process the data received from the input layer. Similarly, the next hidden layer computes the output and the last layer processes this output to produce the final result. The final result is computed by hidden and output layer using transfer functions. The first step in the ANN is training. An input is fed to the ANN along with the target outputs and the weights are set randomly, initially. The training of the network is stopped when the desired level of performance is achieved. The weights computed during this stage are used to make decisions in the evaluation of output [9] [10] [11] [15].

In this study, the neural network code in Matlab was used for ANN training and testing. The ANN analysis using Feedforward Back Propagation (BP). The ANN model optimization is based on the type of training algorithm Levenberg-Marquardt (LM) and the number of neurons in the hidden layer [13] [26]. The input layer has three neurons represented the cutting speed feed rate and axial depth of cut, and the output is surface roughness. The activation function used in the hidden layer and output layer during training and testing is tansig. The ANN predicted values was determined from 18 data experimental results. Before training and testing networks, the normalization of input and target data is in the range of -1 and +1, with equation (4).

$$x_i = \frac{2}{(d_{max} - d_{min})}(d_i - d_{min}) - 1 \tag{4}$$

where, d_{max} and d_{min} are the maximum and minimum values of the row data, d_i is the input and output data set. To evaluate statistical network performance commonly are used functionally Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE). The error functions which are defined by equations (5) and equation (6).

$$MSE = \left(\frac{1}{N}\right) \sum_{N=1}^{N} |t_i - o_i|^2 \tag{5}$$

$$MAPE = \left(\frac{1}{N}\right) \sum_{N=1}^{N} \left|\frac{t_i - o_i}{o_i}\right| \tag{6}$$

where, *t* is the target value, *o* is the output value, and *N* is the number of experiments. Train each network, the performance goal value (MSE) was set to 0.00001 and the maximum number of epoch train is 5,000. The minimum performance gradient is 1e-7, initial μ is 0.001, μ decrease and increase factor are 0.1 and 10. There is no standard rule about the number of hidden layers, it depends on the specifications and complexity of the experimental data. Many researchers only use one hidden layer to obtain optimal conditions [26] [27] [28]. The number of neurons in the hidden layer was determined from figure3. Network of structure 3-12-1 for mineral oil and 3-16-1 for coconut oil were best for representing training performance.

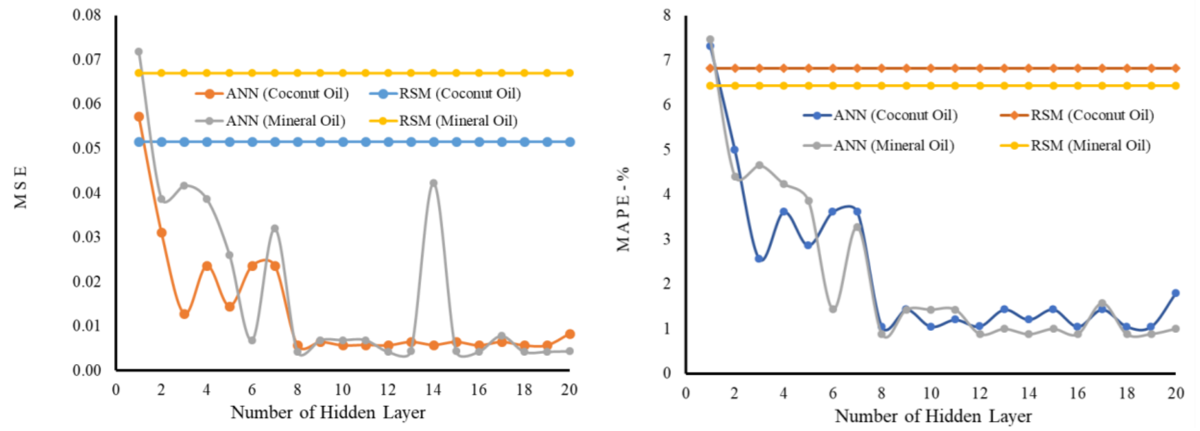
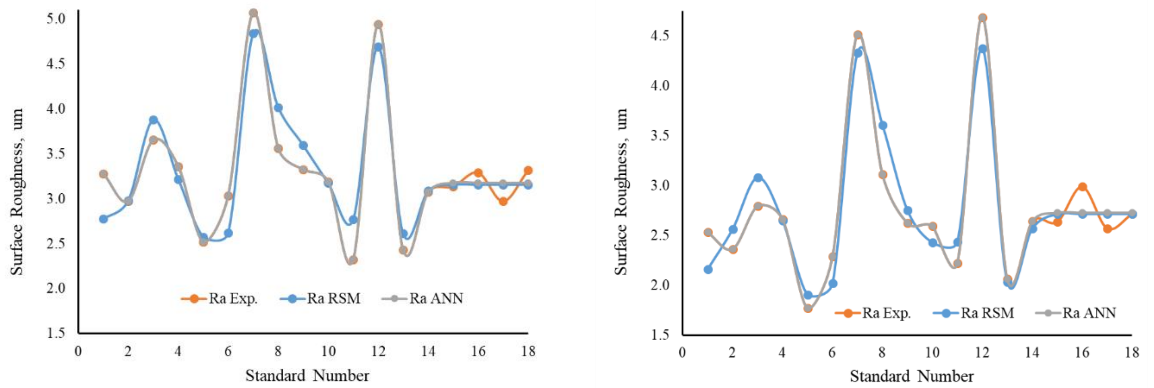


Figure 3. MSE and MAPE variation in prediction with number of neurons

Plot experimental surface roughness values and prediction from RSM and ANN is given in figure 4. It has been found that the predicted surface roughness of the ANN model gave better accuracy than the RSM model. These results were also reported by the [27] [28].



Mineral Oil Coconut Oil

Figure 4. Surface roughness of experimental and prediction results based on RSM and ANN

4. Conclusion

In this study, it presents RSM and ANN applications to predict and optimize machining parameters to improve surface finish. Both of RSM and ANN produce a predicted value very close to the experimental values. Machining using coconut oil as a cutting fluid is better than mineral oil (16.71%). ANN structure 3-12-1 for mineral oil and 3-16-1 for coconut oil showed better performance than RSM prediction. The effect of machining parameters on surface roughness that with increasing cutting speed surface roughness value is smoother. And it increased significantly with increasing feed rate and axial depth of cut. The optimum machining parameters for the lowest surface roughness for cutting speed, feed rate, and axial cutting depth are 31.11 m/min, 0.05 mm/tooth and 5.0 mm with surface roughness values 2.98 µm (mineral oil) and 2.565 µm (coconut oil).

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