International Journal of Scientific & Engineering Research, Volume 8, Issue 5, May-2017
ISSN 2229-5518

Prediction of Surface Roughness using an Artificial Neural Network in Turning Al based Metal Matrix Composite with coated carbide insert

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Abstract--- Surface roughness is considered as one of the most important parameters in the industrial field. In the present study, a model has been developed using the artificial neural network to predict surface roughness for turning of 5052 Aluminium alloy matrix reinforced with 15% Silicon Carbide (SiC). Different values of cutting speed and feed rate have been considered as input variables under both dry and wet condition to obtain the desired surface roughness as output. Lowest MSE (0.0052) has been found under wet condition while using 19 neurons and log-sigmoid transfer function in the hidden layer. A feed forward multi-layer neural network having 2-19-1 structure has been selected as the optimum network. The correlation coefficient, R=0.997 proves the ability of the model to predict accurately. The impact of input variables (cutting speed, feed rate, and cutting condition) on surface roughness is analyzed by graphical representation. Finally, the model can be used to predict surface roughness in different cutting condition and will help to find out the behavior of surface roughness under various cutting variables.

Index Terms—ANN, Coated carbide insert, Dry and wet condition, MMC, Mean square error, Surface roughness, Turning.

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1. Introduction

Since the beginning of civilization, the production and application of materials have been fundamental to industrial activity. More recently the composites industries have largely set the pace for the integration of technical progress in the economy. A composite material is made by combining two or more materials and these two materials work together to give the composite unique properties. Composites are lightweight, strong and environmentally friendly. That is why these materials are used in aircraft structure and as aerospace components. The varieties of composite material are very wide and metal matrix composite (MMC) is one of them. A metal matrix composite (MMC) is a composite material with at least two constituent parts, one being a metal. The other material may be a different metal or another material, such as a ceramic or organic compound. They are made by dispersing a reinforcing material into a metal matrix. It is one of the most popular composite materials because it has some potential properties. These excellent properties include high strength & stiffness, excellent fatigue resistance, high heat resistance, high wear resistance, high corrosion resistance, low weight, improved elevated temperature properties, improved thermal expansion, and improved wear resistance. MMCs are widely used in defense, missile components, tank components, aerospace, space structure, speed brake, hydraulic components, helicopter components etc. The most common example of MMC is an aluminium matrix composite reinforced with silicon carbide (Al-SiC). Its strength to weight ratio, which is three times more than mild steel is the most important property of aluminium-silicon carbide with reference to the aerospace industry [1]. Also, those composites which contain Silicon carbide as reinforcing material and Aluminium as a matrix have high modulus, strength values, wear resistance, high thermal stability, less weight and a more effective load carrying capacity compared to many other materials [2, 3]. But one of the major problems in machining particulate metal matrix composites is surface roughness and sub-surface damage which leads to an uneconomical production process. Surface roughness uses as an important factor to consider the performance of machining process and it also reflects the quality of the product. That is why many researchers have been extensively studied to identify the required machining parameters for optimum surface roughness. Kilickap et al. [4] investigated on tool wear & surface roughness while machining 5% SiC-p Al-MMC. They concluded that the most influential machining parameter is cutting speed and the second influential machining parameter is feed rate. Palanikumar and Karthikeyan [5] studied the factors influencing surface roughness on the machining of Al/SiC particulate composites. It was recommended that using coated carbide cutting tool, high cutting speed and low feed rate helps to get the better surface finish. They used response graph, response table, normal probability plot, interaction graphs and analysis of variance (ANOVA) technique to optimize the cutting parameters like feed rate, cutting speed, % volume fraction of SiC to attain minimum surface roughness.

To identify suitable parameters for achieving required surface finish is very difficult and for this reason researchers have developed many different prediction models by using various methodologies like Taguchi method, Response

ISSN 2229-5518

Surface Method (RSM), multiple regression techniques, Artificial Neural Network (ANN), Fuzzy Logic (FL), adaptive neuro-fuzzy inference system (ANFIS). Manna A. and Bhattacharyya B. [6] used Taguchi method to optimize the cutting parameters for the effective turning of Al/SiC-MMC using a fixed rhombic tooling system. Barman and Sahoo [7] experimentally studied the fractal dimension of aluminium, brass and mild steel in CNC turning and applied both ANN and RSM models to predict the dimension. They concluded that ANN models work better than response surface models to predict accurately. Erzurumlu and Oktem [8] also concluded the same result by stating that ANN model gives more accurate Ra prediction values than any other conventional model. ANN is also better than linear regression analysis and utilizes only a few training and testing data set to make an accurate prediction of surface roughness [9, 10]. A number of researchers have compared artificial neural network with response surface model and concluded that ANN models predict the surface roughness with better accuracy than RSM models [11,12]. So it can be concluded that ANN models are very effective and popular for predicting surface roughness accurately.

The popularity of MMC is increasing everyday but it has been found that very limited works have been done to predict and optimize the process parameters in machining of Al based MMC. Researchers have performed drilling and end milling operation on MMC and reported that surface roughness is influenced by cutting speed and feed rate [13, 14]. Devarasiddappa et al. used ANN model for predicting surface roughness for end milling of Al-SiCp material matrix composites and reported that surface roughness is mainly affected by feed rate [15]. A. Dolatkhah designed the formation process of Al5052/SiC composite and showed that change of tool rotational direction between FSP passes, increase in a number of passes and decrease of SiC particles size enhance hardness and wear properties [16]. No study is still found which determines the optimum process parameters in turning of Al5052/SiC metal matrix composite. In this paper, an artificial neural network model is presented to predict the surface roughness for turning of MMC having 5052 Aluminium alloy matrix reinforced with 15% Silicon Carbide (SiC) turned in both dry and wet condition with coated carbide insert and then results are compared. The effect of cutting speed and feed rate is studied. In addition to the two basic machining parameters another variable cutting condition is also considered in the present study.

2. Experimental Study

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The work piece material used throughout the project was manufactured by using the CO2 molding and stir casting process. The matrix composition of the work piece was 5052 aluminium alloy reinforced with 15 vol. % of particulate silicon carbide (SiC). The chemical composition of the work piece material is shown in Table I. The machining test has been carried out by straight turning of Aluminium 5052 MMC bar (diameter 100 mm, length 260 mm with 30 mm boring) in a reasonably rigid and powerful lathe machine (7.5 kw, China) by standard coated carbide insert (SNMG) at different cutting velocity (Vc) and feed rate (So) under both dry and wet condition. A schematic diagram of the experimental set-up is shown in figure I. For wet condition, VG-68 cutting oil has been delivered. The depth of cut was maintained constant at 1 mm throughout the experiment.

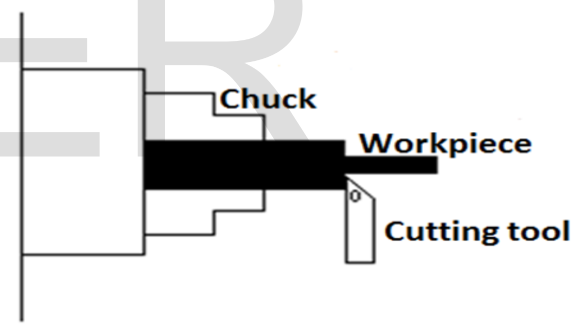

Fig 1: Schematic diagram of experimental set-up

TABLE 1: Chemical Composition (wt%) of 5052 Aluminium Metal Malrix Composile (MMC)

Alloy	Mg	Cr	Mn	Cu	Fe	Zn	Si	Al
5052Al MMC(15% SiC)	0.25	0.30	0.10	0.10	0.40	0.10	0.25	Remain

The cutting conditions used for machining alumimum 5052 MMC with carbide tool (SNMG 120408, Sandvick) is given below in table II. After each trial, the value of surface roughness for several conditions was measured by Surface Roughness Tester (Phase-II SRG-4500, Portable Tracing speed: 0.5 mm/s (length 0.8 mm) Accuracy: <- ±10% Pick-up-stylus: Diamond). To analyze the effect of input variables (cutting speed, feed rate) on surface roughness, a full factorial method is used. The design of experiments helps to identify the significant inputs and also to achieve an optimal output. It is also used to understand the effect of two or more independent variables upon a single dependent variable. In this study, this method is used to make all the possible combinations of input variables and determines 15 (3Vc X 5f) numbers of observation for each of the cutting conditions

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(Dry and Wet). Table 3 shows 30 numbers of experimental results for each cutting condition (dry and wet).

TABLE 2: Experimental Conditions

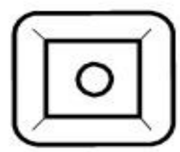
Machine Tool	:	Lathe machine (China) ,7.5 kW
Work Material	:	MMC
Cutting Tool	:	 SNMG 120408, Sandvick
Geometry	:	-6°, -6°, 6°,6°, 15°,75°, 0.8 mm
Tool Holder	:	PSBNR 2525 M12 (ISO specification) Sandvick
Process Parameters		
Cutting velocity (Vc)	:	78 , 84 ,120 m/min
Feed rate (So)	:	0.10, 0.12 , 0.14 , 0.16, 0.18 mm/rev
Depth of cut (d)	:	1 mm
Environment	:	Dry and Wet

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TABLE 3: MACHINING RESULT AND VALUES OF SURFACE ROUGHNESS (RA)

Trial no	Cutting Condition (CC)	Cutting Speed (Vc)	Feed (So)	Surface Roughness (Ra)
1	Dry	78	0.10	2.40
2	Dry	78	0.12	2.45
3	Dry	78	0.14	3.28
4	Dry	78	0.16	3.40
5	Dry	78	0.18	3.54
6	Dry	84	0.10	2.70
7	Dry	84	0.12	2.78
8	Dry	84	0.14	2.89
9	Dry	84	0.16	2.90
10	Dry	84	0.18	3.00
11	Dry	120	0.10	2.70
12	Dry	120	0.12	2.91
13	Dry	120	0.14	3.14
14	Dry	120	0.16	3.21
15	Dry	120	0.18	3.22
16	Wet	78	0.10	1.10
17	Wet	78	0.12	1.12
18	Wet	78	0.14	1.22
19	Wet	78	0.16	1.34
20	Wet	78	0.18	1.40
21	Wet	84	0.10	1.20
22	Wet	84	0.12	1.22
23	Wet	84	0.14	1.59

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24	Wet	84	0.16	1.66
25	Wet	84	0.18	1.86
26	Wet	120	0.10	1.40
27	Wet	120	0.12	1.54
28	Wet	120	0.14	1.74
29	Wet	120	0.16	1.89
30	Wet	120	0.18	2.10

3. ANN STRUCTURE

Artificial Neural Networks are models inspired by the neural structure of the brain. The objective of the neural network is to transform the inputs into meaningful outputs. An artificial neural network is composed of many artificial neurons that are linked together to determine the relation between input and output. A neuron is the fundamental processing element of a neural network. Neurons of input layer receive input value, transmit them to hidden layers which are multiplied by respective weighing factors and biases, these products are simply summed, fed through a transfer function to generate a result and then output layer shows some numerical value of responses. The basic units of the neural network are the structure of the network, training algorithm, training time, training and testing data size, learning function, transfer function, values of weights and biases and performance function. In the present study, a feed forward multi-layer neural network has been developed to predict surface roughness and the architecture of the ANN modeling is illustrated in Figure 2.

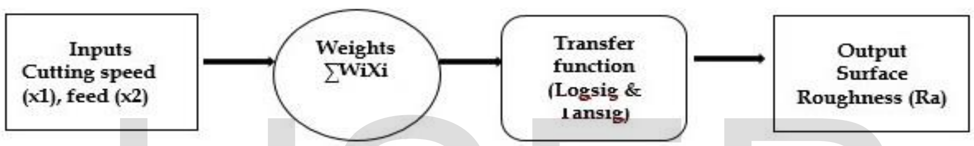

Fig 2: ANN Structure

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3.1: STRUCTURES OF ANN MODEL

The selection of the number of hidden layers is very important to obtain an accurate result. Multiple hidden layers can be used to define different structures. Grzesick and Brol [17], for example, applied the 7–72–72– 72–7 structure meaning that it has three hidden layers with 72 neurons for each layer. A.M. Zain et. al. used one hidden layer and showed that it is sufficient to predict with higher accuracy [18]. Two 2-n-1 structures were used in this study wherein one for dry and another for wet condition. For input layer two variables (cutting speed and feed) and for output layer one variable (surface roughness) was considered and the value of these variables are shown in table 3.

3.2: NUMBER OF TRAINING AND TESTING DATA

It is very difficult to decide the adequate number of neurons for the required result. Trial and error method is used for deciding the number of neurons on the basis of the improvement in the error with increasing number of hidden layers [19]. Also, a number of trials can be made by altering neuron number from 1 to 30 for getting the least MSE and acceptable predicted output [12]. In the present study, MSE of the networks are calculated from one (01) neuron and gradually increased to a maximum of twenty (20) neurons.

Table 4 shows 30 available experimental samples wherein 15 samples are for dry and another 15 samples are for wet condition. Some recommended ratios of training and testing samples are 90%:10%, 85%:15% and 80%:20% with a total of 100% for the combined ratio [20]. In this case, for both Dry and wet model, the selected ratio is 80%:20%. So the amount of data used to train and test the network is:

1. (80/100) x 15 = 12 training samples,
2. (15/100) x 15 = 3 testing samples.

Among the values are shown in table 3, three experimental results (3rd, 8th and 14th) were used for testing the dry model and other three (20th, 24th, 28th) for testing the wet model. Rest of the values were used to train the network.

3.3: TRAINING ALGORITHMS

To train the network different types of the algorithm can be used such as Levenberg-Marquardt (trainlm), Scaled Conjugate Gradient (trainscg), Bayesian Regularization (trainbr) and they have competitive advantages over one another. The Bayesian Regularization algorithm minimizes a combination of squared errors and weights and then determines the correct combination so as to produce a network that generalizes well [21]. In this study, Bayesian Regularization (trainbr) has been used to train the neural network of MATLAB R2015a toolbox to predict the surface roughness. BR it can produce more accurate results than Levenberg– Marquardt algorithm in case of operating with a low amount of training data.

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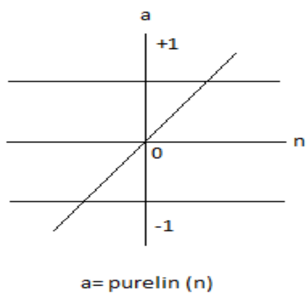
. 3.4: TRANSFER FUNCTION, TRAINING FUNCTION, LEARNING FUNCTION AND PERFORMANCE FUNCTION

The log-sigmoid transfer function (LOGSIG) is one of the most commonly used transfer function, which takes the input and transfers the output into the range 0 to 1. Another popular transfer function is hyperbolic tangent transfer function (TANSIG) in the term of neural networks which has an output in the range of -1 to +1. In the term of correlation coefficient both LOGSIG and TANSIG shows similar reaction But it can be concluded that LOGSIG will perform better than TANSIG when the correlation is high and as performance function RMSE is considered [22].

(a)



(b)

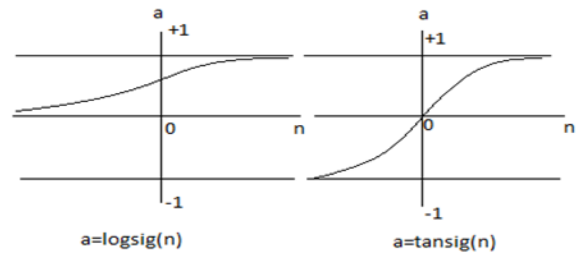


Fig 3(a-b): Linear transfer function, Log-sigmoid transfer function and hyperbolic tangent transfer function

For this study, both Log-sigmoid (logsig) and hyperbolic tangent sigmoid (tansig) transfer function have been employed in the hidden layer, whereas the pure linear function (purelin) has been used in the output layer. The graphical representation of the transfer functions has been shown in figure 3. The mathematical equations for these transfer functions are:

$$\text{tansig}(n) = \frac{2}{1+e^{-2n}} - 1 \qquad (1)$$

$$\text{logsig}(n) = \frac{1}{1+e^{-n}} \qquad (2)$$

'Learngdm' is the gradient decent with momentum weight and bias learning function which has been used here. Some popular performance functions are mean absolute error (MAE), sum square error (SSE), root mean squared error (RMSE) and mean absolute percentage error (MAPE). Since the mean square error (MSE) is the most commonly used performance function by researchers that is why it is recommended to apply for determining the error in the predicted value of surface roughness [23]. So, MSE has been used to determine and compare the errors to get the lowest error. Table 4 shows the testing error and the calculation is done by using the following equation:

$$\text{MSE} = \frac{1}{N}\sum\{\text{Ra (actual)} - \text{Ra(predicted)}\}^2 \qquad (3)$$

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4. RESULTS AND DISCUSSION

In this work, different neural architectures were developed to achieve the optimum number of neurons and transfer function for hidden layer. Finally an architecture has been selected based on the least MSE in the testing data and suggested to use this architecture for predicting surface roughness in the particular case. Table 4 shows that the least MSE can get by using log-sigmoid (logsig) transfer function and 19 number of neurons in hidden layer for both dry and wet model.

Finally 2-19-1 revealed the lowest mean square error (MSE) for both dry (0.0211) and wet (0.0051) condition assisted turning. In addition, the mean absolute percentage errors (MAPE) are calculated for both models. The MAPE for the dry model is 4.47% while for the wet model it is 3.61%.

A deviation graph for the selected network is plotted to show the difference between the actual and predicted average surface roughness parameter for both dry and wet condition. In fig. 4 (a), variation for the dry condition is shown in the y-axis and the experimental runs, here which is 15 runs, along with the x-axis. Fig. 4 (b) reveals the situation of wet condition.

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TABLE 4:
MSE OF SURFACE ROUGHNESS USING OPTIMAL NUMBER OF NEURONS AND TRANSFER FUNCTION FOR HIDDEN LAYER

Network Structure	Dry Condition		Wet Condition	
	Logsig	Tansig	Logsig	Tansig
2-5-1	0.093738927	0.064925053	0.065403593	0.059826786
2-6-1	0.051163953	0.039368409	0.06094902	0.073181466
2-7-1	0.043438248	0.043694879	0.044008062	0.048587876
2-8-1	0.055906353	0.067213142	0.059592647	0.048334153
2-9-1	0.054344967	0.05082795	0.055993007	0.045787274
2-10-1	0.082634162	0.065308041	0.052451998	0.041549824
2-11-1	0.056175532	0.076857975	0.042431097	0.043547445
2-12-1	0.063680047	0.040564869	0.035172359	0.047632058
2-13-1	0.041656403	0.064225165	0.035672452	0.077290029
2-14-1	0.054483483	0.032421109	0.035110308	0.037816145
2-15-1	0.043846914	0.049252994	0.044724401	0.03952452
2-16-1	0.030775179	0.042006977	0.023692867	0.03939962
2-17-1	0.049912908	0.049817825	0.042916003	0.047034609
2-18-1	0.042421448	0.052689534	0.023811243	0.047810811
2-19-1	0.021116013	0.043310844	0.005165807	0.045959587
2-20-1	0.036550703	0.061147499	0.044120203	0.051810963

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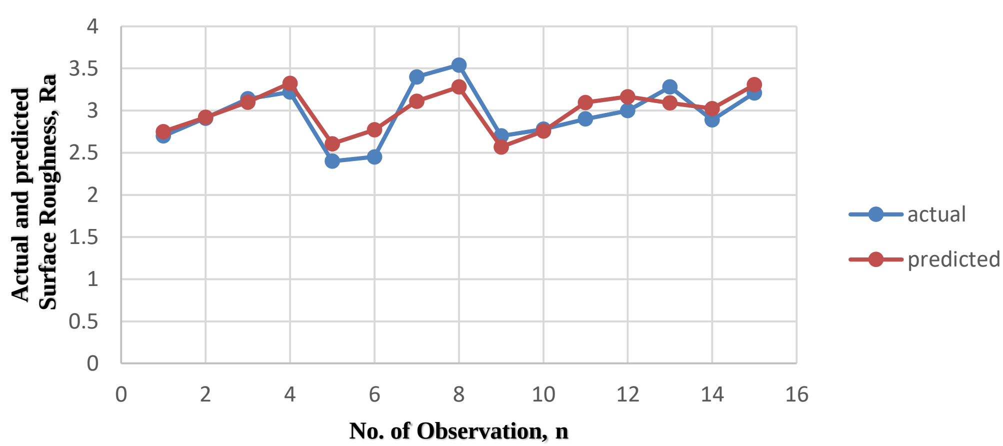

Fig 4 (a): Comparison between Actual and Predicted surface roughness in Dry condition (2-19-1)

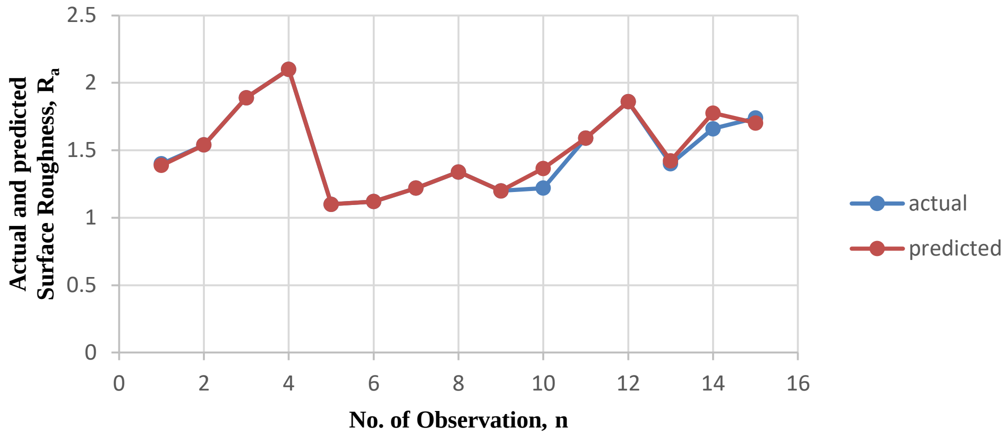

Fig 4 (b): Comparison between Actual and Predicted surface roughness in Wet condition (2-19-1)

With the correlation coefficient R, ANN models prove that the model prediction reveals a close relationship with the experimental result. Fig. 5(a) shows that the R-value is 0.95898 when the network was tested with nineteen number of neurons and log-sigmoid transfer function in a hidden layer under dry machining and R-value is 0.9919 on wet assisted machining which is illustrated in Fig. 5(b). The correlation coefficient is a quantity that gives the quality of the least squares fitting to the original data. If the R-value is 1 then it indicates the perfect correlation between measured and predicted values. R-value close to 1 represents that the data is closest to the line of best fit. The network architecture 2-19-1 shows the best value of R for wet condition.

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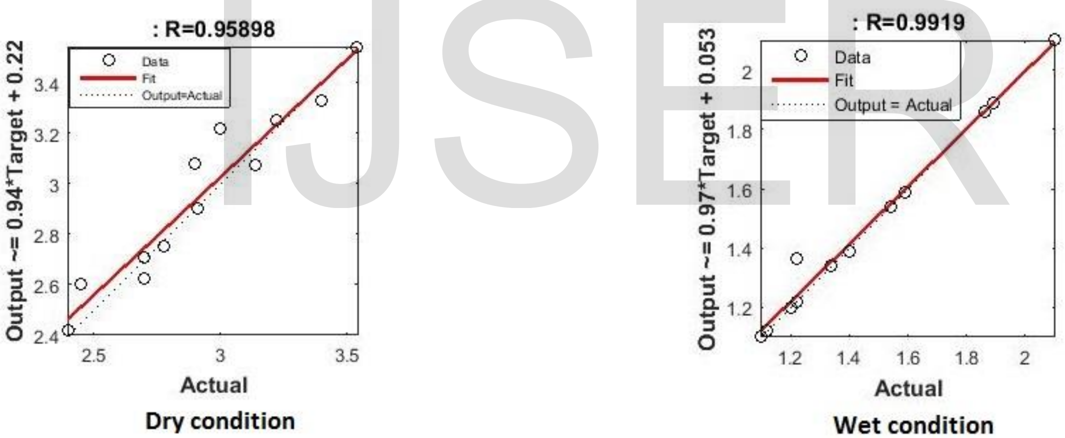

(a) (b)

Fig 5(a-b): Regression curve between predicted and actual surface roughness

The relation of surface roughness with input variables (cutting speed, feed rate) is investigated by plotting in the graphs. The roughness plots for dry turning in Fig. 6(a) and 7(a). Fig. 6(b) and Fig. 7(b) show the same for turning in wet condition. It can be observed that the values of surface roughness in wet condition are better than the value obtained from dry turning. From the fig 7 (a) and 7 (b) it can be shown that the surface roughness increases as the feed rate increases. The surface roughness parameter is found, in Fig 6(a), to decrease with increasing cutting speed. It is reported that the high cutting speed induces extra hardness within the material which helps to produce less roughness [24]. On the other side fig 6(b) depicts that surface roughness while turning in wet condition increases as the cutting speed increases.

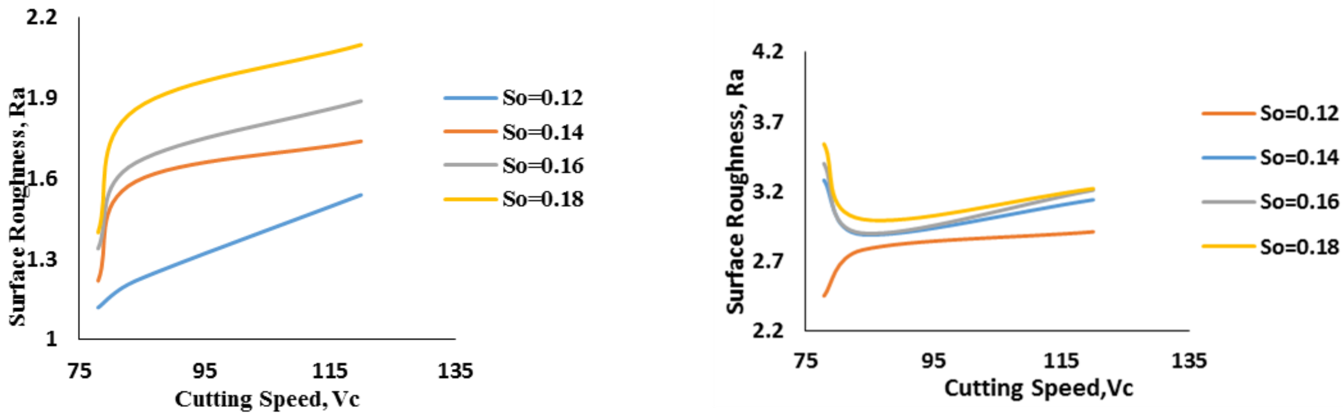

Figure 6 (a-b): Variation of surface roughness with cutting Velocity at different feed rate at a) dry and b) wet condition

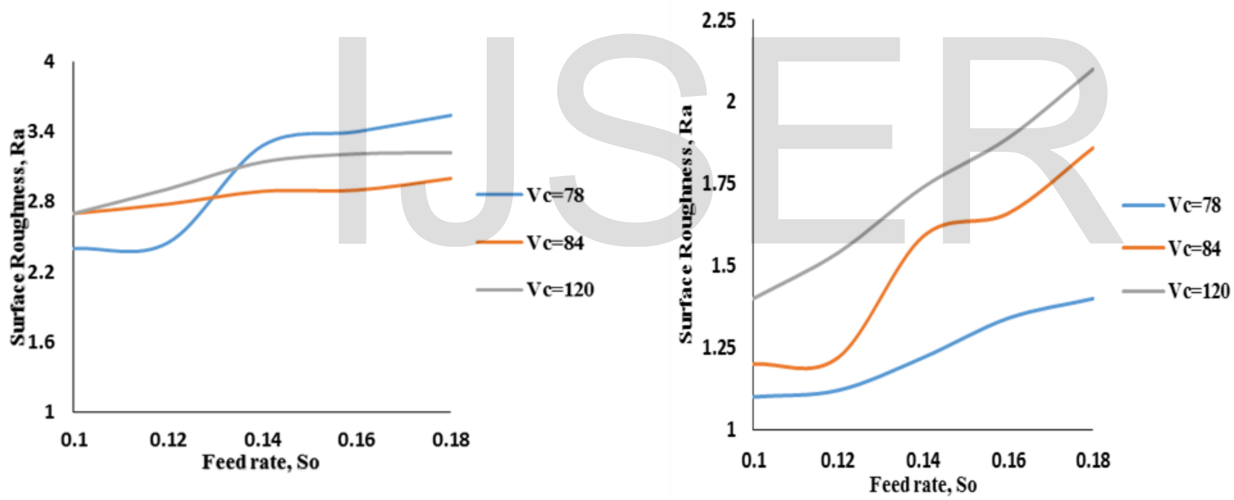

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Figure 7 (a-b): Variation of surface roughness with feed rate at different cutting speed at a) dry and b) wet condition

5. Conclusion

The objective of this work was to develop an artificial neural network based surface roughness prediction model for Al-SiCp MMC turning with carbide tool under both dry and wet condition. A better predictive model helps to select the optimum machining parameters before performing machining operations.

The multilayer feed forward network consisting of two inputs (cutting speed, feed rate), 19 hidden neurons (log-sigmoid transfer function) and one output (Surface roughness) was used to develop the models and 2-19-1 was found to be the optimum network architecture for the models. A good performance of the neural networks has been achieved with the lowest mean square error being 0.0211 (dry) and 0.0051 (wet) when compared with the experimental values. The wet model reveals the superiority of the ANN model (3.61%) as the MAPE, in this case, is lower than the dry model (4.47%). . The correlation coefficient has been found 0.9919 for a wet condition which reflects a good fit of the prediction models. These results show that the ANN model can be used easily for prediction of surface roughness in turning Aluminium based MMC by coated carbide insert under both dry and wet environment.

Finally the variation of surface roughness with the input parameters has been plotted in the graphs for both dry and wet condition. It can be concluded that in dry condition surface roughness increases directly with feed rate and maintains an inverse relationship with cutting speed. On the other contrary, surface roughness bears direct relation with both cutting speed and feed rate in wet condition.

This model can be used to predict of surface roughness in turning. So, as a whole, it can be used to evaluate the surface roughness before the machining of the part and the observation of the behavior under different cutting condition helps to obtain the desired surface roughness.

ACKNOWLEDGMENT

The authors are thankful to Bangladesh Industrial and Technical Assistance Center (BITAC) and the Department of Industrial and Production Engineering, BUET, Dhaka, Bangladesh for providing laboratory facility for performing the research work.

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