Artificial Neural Network-Based Modeling of Surface Roughness in Machining of Multiwall Carbon Nanotube Reinforced Polymer (Epoxy) Nanocomposites

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In the manufacturing process, the surface roughness acts as one of the vital response to define the machined product quality.This manuscript platforms on the modeling of surface roughness(Ra) during milling of Multiwall Carbon Nanotube (MWCNT) reinforced polymer nanocomposites using an artificial neural network (ANN). ANN developed as a cost-effective approximation module that is competent of self- learning and pliable to complicated data variables.Taguchi based L27 orthogonal design was perfectly utilized to perform the machining operation. The consequence of process parameters, i.e., MWCNT (wt.%), Spindle speed (N), Feed rate(F), and depth of cut (D) have been investigated to attain the minimalRa of the machined samples.The ANOVA study shows that Feed rate(F) has the most significant (55.25%) parameters for Ra followed by Spindle speed (N), MWCNT weight percentage (wt.%), and depth of cut(D). The Feed forward back propagation network is used for the ANN model with TRAINLM and LEARNGDM functions used as training and learning algorithms.The selection of an adequate model based on the correlation coefficient (R^2), mean squared error (MSE), and the average percentage error (APE) was achieved. The designated model has high accuracy with R^2> 99%, MSE < 0.2%, and APE < 3%,.Further,the plot between experiment value and predicted value shows the adequacy and feasibility of the proposed ANN model in the machining environment.

Keywords: *ANN, MWCNT, Nanocomposites, Milling, Surface Roughness.*

1. INTRODUCTION

The polymer composites possess a wide range of applications in aircraft, automobile, space, sensors, PCB, biomedical industries [1]. In this series, MWCNT plays a vital role in the carbon family to improve the mechanical and chemical properties of the composites. The nano-size carbon reinforcing agent into the epoxy matrix creates better dispersion and high aspect ratio that enrich the synergetic effect. This effect is highly required in high-performance and multifunctional applications like sensors, biomedical, aviation, textile sectors, etc. Also, these nanocomposites possess relatively reduced weight and high strength and high fatigue and creep resistance t to confirm economic efficiency and safety issues [2-4]. Carbon nanomaterials exhibit extraordinary electrical, magnetic as well as mechanical properties. The high aspect ratio of the carbon nanomaterials makes them a primary candidate to strengthen the thermoset epoxy matrix for various industrial applications. The standard reinforcement from the nanocar–bon family is a single-wall carbon nanotube (SWCNT), MWCNT, carbo nanofiber, graphene carbon dots. These carbon nanomaterials enhance the desired properties by adding in little quantity. Sometimes inappropriate ratio can create the chance of agglomeration that deteriorates the mechanical features. Romha´ny et al. [5] evaluated the mechanical properties of MWCNT filled polymer(epoxy). They noticed that bending modulus increases by 10%, Young's modulus by 12%, and impact strength by 20%; however, tensile strength has decreased by 4.6%. Hadavand et al. [6] reinforced distinct weight ratios(0.1–0.3 wt.%) of treated MWCNT and untreated MWCNT into polysulfide resin and observed that fracture strain from 0.16% to 0.25%, tensile strength from 5.29 to 8.83 MPa, and Young's modulus from 458 to 723 MPa. Tariq et al.[7] fabricated multi-scale reinforcement composites by MWCNT and carbon fabric in an epoxy matrix and during their mechanical characterization, it was found that flexural strength improved by 54% and tensile strength by 60% with reinforcing small amounts (0.25%) of MWCNTs into CFRP. Kalakonda et al.[8] developed MWCNT dispersed thermoplastic polyurethane and 200-fold over in tensile modulus at 19% MWCNT loadings than pristine epoxy. Leopold et al. [9] added nanotubes into the epoxy and found that it led to increases in Young's modulus and toughness of the nanocomposites. The application of MWCNT /polymer composites has broad application potential as electronic packing, shielding, storage capacitors, and for structural use.

Generally, polymer composites fabricated near net shape, but secondary machining procedures such as

Received: March 2020, Accepted: June 2020
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doi: 10.5937/fme2003693K

turning, drilling, and milling are highly required to assemble the finished product into the main component for final assembly. Surface roughness (Ra) is one of the leading quality performance indexes of a machined part that characterizes surface geography in manufacturing science. The tool geometry, work-tool materials, cutting parameters, and statistical variation are profoundly affected during the manufacturing process. In industries, surface features are the basic description of finish quality product, and it is essential for different engineering products and other aesthetic requirements. The reasonable surface roughness is desirable to enhance the covering appearance and tribological aspects, while disproportionate surface roughness comprises higher machining costs.

From prior work, it could be narrowed down that Ra is the main factor that directs the relics, as mentioned earlier. Hence, it becomes the significant demand of the hour to optimize the desired performances of surface roughness during machining (milling, drilling, turning, etc.) of polymer nanocomposites. During the machining process, various quality and productivity characteristics drastically influenced by speed, feed rate, depth of cut [10-11]. There are many machining performance optimization attempts performed bypioneer researches**.** Gopalsamy et al. observed the machinability aspects of hardened steel to attain optimal parametric combinations through the GRA module. They effectively introduced the Grey concept to examine the influence of machine constraints such as cutting speed, feed, cutting depth and cutting width on machining performances such as MRR, Ra, TWR. They were analyzed Tool wear pattern using optical microscopy investigations, SEM, and X-ray diffraction method (XRD). Finally, they have achieved a comparative study between rough machining and finish machining [12]. Fong and Ming-der carried out the experimental analysis with CNC milling machining for enhancement of the process adaptability, flexibility, and robustness. They have effectively implemented the Taguchi method combined with a suggested ideal function module used to identify optimal process parameters in high-speed CNC milling. Also, three typical geometries (square, circle, and triangle) were used to represent the geometric variants of the mold and die products. Experimental results revealed that the machined product dimensional accuracy has significantly enhanced by optimal conditions [13]. Panshetty et al. performed CNC machining by considering Taguchi based orthogonal design. In this study, milling, performance optimization has been done to get the optimum values for the surface finish and rate of material removal. The impact of speed, rate of feed, cutting depth on machining performances has been considered to develop the mathematical modeling between them. It has been found that speed acts as the major attribute for surface roughness and material removal rate[14]. The various eminent scholars have used different tools and techniques to establish predictive models across multiple machining procedures. In the field of manufacturing, the ANN modeling is widely used for the investigations of machining performances like Ra, rate of material removal, thrust, cutting force, tool wear and its life, etc. [15]. A procedure that entails small size data set for biological neurons was utilized by Kohli et al. [16]. Risbood et al. [17] established a steel turning operation with four process parameters using High-Speed Steel (HSS) tool. The machining responses analyzed are surface roughness and dimensional indices to evaluate the quality of the turning samples with the help of a multilayer perceptron (MLP) model. The outcomes of the turning process scaleup that the proposed model augments well with the desired values. Krzywanski et al. [18] investigated the coefficient of heat transfer in the combustion chamberof the mixing fluidized bed boiler. ANN modeling was used efficiently to appraise the heat coefficient value. The outcomes of the study demonstrate that ANN gives quick and precise results in comparison to numerical models developed earlier. Manish et al. [19] performed machining of composite beams and proposed an ANN model for the prediction of machining induced damage, i.e., delamination. Tsai et al. [20] evaluated the machining performances during the Electro discharge machining (EDM) process and established a neural network between inputs and responses. It was noticed that RBFN gives the desired results with little errors. The proposed model validated the feasibility of the ANN module. Zain et al. [21] depicted an ANN model to envisage the surface roughness of the machined components during the milling operation. It is observed that for achieving a lower value of surface roughness, low feed rate with high speed and low radial angle plays a primary role. Artificial Neural Networks (ANNs) are intricate mathematical models that imitate successfully mimic biological neural networks. ANNs are often favored over regression model optimization and prediction purposes for the noisy data. ANNs were used for optimizing and prototypical highly" complex and nonlinear biological processes [21-25].

From the literature work underwent for purpose, it has been observed that eminent scholars did ample practice in the machining of polymer composites, but very limited data are available on modeling and simulation of the machining process. But it has been realized that machining behavior of MWCNT polymer composites is by-passing through an openingstage, work is not satisfactorilyprospered in this area. However, it is widely used in the fabrication of various components in aviation, battery applications, sensors, biomedical devices, circuit boards, automotive parts, and other multifunctional engineering components. Hence it can become a potential area of research for academia, industry, and research organization. The application of ANN modeling was not performed by any scholars earlier for machining of MWCNT nanocomposites. Therefore, the present work explores the biological behavior of the neural networks to calculate the surface roughness for the enhancement of the quality of the machined product. ANN modeling is proposed to control the varying constraints for the optimized value of the machined surface.It is directly responsible for the quality and productivity functions of any machined product. Taguchi based L27 orthogonal array (OA) was employed to layoutmilling experimentation. An attempt has been made to investigate the machining behavior of nanocomposites for the minimal values of surface roughness.

2. EXPERIMENTAL DETAILS

The milling experiment was performed on MWCNT reinforced epoxy composites with Taguchi based L27 OA. The composites were developed by the solution casting method. The three-varying wt.% of MWCNT (0.5%,1.0%,1.5%) was used to reinforced into epoxy (Lapox, L-12). The nano reinforcement is having an average length of 15 µm and an average diameter of 10-15 nm, and the X-ray diffraction (XRD) pattern, as displayed in Figure 1. It gives the extent of graphitization and CNT degree with the highest peak at 26.2 and lowest at 30 degrees that validates the graphitic plane existence. The milling experiment was performed on the Vertical CNC setup Model: TC20-BMV35 (Figure 2). The surface roughness values were levied bythe Surtronic S128 surface roughness tester made by Taylor Hobson (Figure 3).

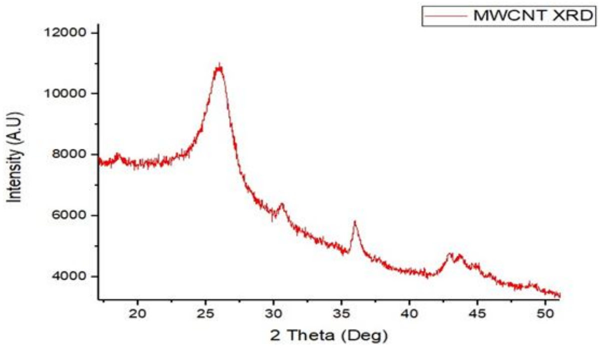

Figure 1. MWCNT XRD result

Figure 2. Vertical CNC milling machine setup

Table 1: Process constraints

Machining Parameters	Symbol	Level 1	Level 2	Level 3
Wt.%	W_t	0.5	1.0	1.5
Spindle Speed	N	500	1000	1500
Feed Rate	F	50	100	100
Depth of Cut	D	1	2	3

For milling experiments, four process parameters were considered, and their variation at four levels was done, as indicated in (Table 1). The milling experiment was based on Taguchi L27 orthogonal array, and corresponding observed data of surface roughness are mentioned in Table 2. The images of machined samples are shown in Figure. 4.

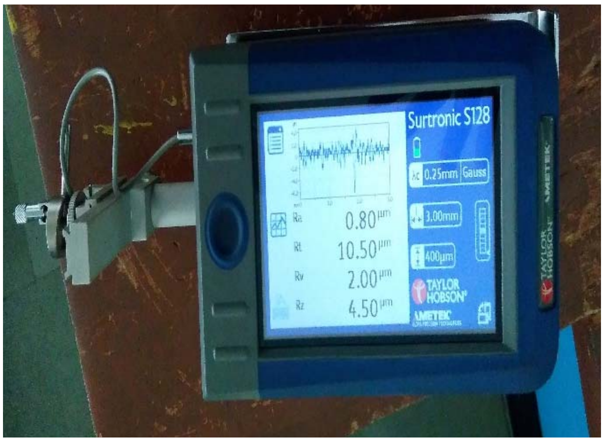

Figure 3. Surface Roughness Tester (Surtronic S128)

Figure 4. Machined Sample

Table 2: L27 orthogonal array and corresponding surface roughness

S.No.	MWCNT weight % (Wt. %)	Spindle Speed (Rpm)	Feed rate (mm/min)	Depth of Cut (mm)	Ra(µm)
1	0.5	500	50	1	2.432
2	0.5	500	100	2	3.613
3	0.5	500	150	3	3.873
4	0.5	1000	50	1	1.908
5	0.5	1000	100	2	2.996
6	0.5	1000	150	3	3.596
7	0.5	1500	50	1	1.888
8	0.5	1500	100	2	2.906
9	0.5	1500	150	3	3.41
10	1	500	50	2	2.473
11	1	500	100	3	3.303
12	1	500	150	1	3.098
13	1	1000	50	2	1.996
14	1	1000	100	3	2.696
15	1	1000	150	1	2.859
16	1	1500	50	2	2.251
17	1	1500	100	3	2.81
18	1	1500	150	1	2.81
19	1.5	500	50	3	2.24
20	1.5	500	100	1	3.256
21	1.5	500	150	2	2.976
22	1.5	1000	50	3	2.068
23	1.5	1000	100	1	2.429
24	1.5	1000	150	2	2.77
25	1.5	1500	50	3	2.043
26	1.5	1500	100	1	2.722
27	1.5	1500	150	2	2.701

3. METHODOLOGY

3.1 Neural Network

A biological network made up of one input layer and one output layer with one or more than one hidden layer. Input layer neurons handover the input variables Xi (i=1,2, 3…n) to neurons of the hidden layer. The following description illustrates the fundamental feature of neural networks.

- Differentiable nonlinear activation function includes each neuron of the network
- The network consists of one or more than one layer, which is hidden from neurons of input and output.
- The degree of connectivity shows by the network, resolute by the connection and synaptic weights among neurons.

The additional function characterized assembly of an artificial neuron (j), which sumps inputs Xi after weighting them with the corresponding weights Wji from the input layer. The weighted sum Sj given as Eq.1

$$S_i = \sum_{i=1}^{n} w_{ji} x_i \tag{1}$$

An activation function f which stimulates the neurons by the following equation:

$$y_i = f\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right) \tag{2}$$

The function f can also be called "Transfer function," The commonly used is the sigmoid function as follows

$$f(x) = \frac{1}{1+\exp(-x)} \tag{3}$$

The training algorithm can use for weight adjustment in ANN. In this context, frequently used the back propagation algorithm for MLP networks [26]. This algorithm defines error function and practice gradient descent to evaluate a set of weights in a specific task [27]. The training of the ANN process forward and backward stage. In the forward phase, fixed synaptic weights for connections between neurons and propagate input signal through the network's layers until it reaches the output layer [28-29]. In the backward stage, generated an error signal by comparing the required response and network's output.

Further, propagate in backward direction through the network's layers. The synaptic weights of the system subject to continuous adjustments in the second phase. The backpropagation algorithm incorporates several types of the algorithm such as gradient descent algorithm, Levenberg–Marquardt, scaled conjugate gradient, resilient backpropagation, and one step secant.

4. RESULTS AND DISCUSSION

After machining of MWCNT/polymer nanocomposites, the surface roughness was observed according to Taguchi based L27 experiments,and ANOVA was effectively done to identify the prominent factor.From Table 3, it wasnoticed that Feed rate(F) has the most significant (55.25%) parameters for Ra followed by Spindle speed (N), MWCNT weight percentage (wt.%), and depth of cut(D).

Table 3. ANOVA For Surface Roughness (Ra)

Source	DF	Seq SS	Adj SS	Adj MS	F-Value	P-Value
Regression	11	7.52888	7.5288	0.68444	41.64	0.000
Wt.	1	0.64832	0.00012	0.00011	0.01	0.934
N	1	0.76963	0.51263	0.51262	31.19	0.000
F	1	4.29597	0.47910	0.47910	29.15	0.000
D	1	0.38623	0.11390	0.11390	6.93	0.019
Wt.*Wt.	1	0.02819	0.02819	0.02819	1.72	0.210
N*N	1	0.32202	0.32202	0.32201	19.59	0.000
F*F	1	0.68209	0.30623	0.30623	18.63	0.001
D*D	1	0.00011	0.01600	0.01600	0.97	0.339
Wt.*N	1	0.04184	0.04184	0.04184	2.55	0.131
Wt.*F	1	0.24970	0.07338	0.07338	4.46	0.052
Wt.*D	1	0.10479	0.10479	0.10479	6.37	0.023
Error	15	0.24657	0.24657	0.01643		
Total	26	7.77545				

For modeling of surface roughness, ANN architecture with one hidden layer was considered. The feed-forward backpropagation network is widely used by research scholars to model various kinds of processes into different fields.In this network,the algorithm subtracts the training response from the target to the obtained error signal. Afterward, it regulates the weights and biases in the input and hidden layers to overcome the error. The structure composed of three-layer, the first layer for four input parameters (MWCNT wt.%, spindle speed, feed rate and depth of cut) and the second layer for is the hidden layer with j neurons and the third layer is output layer for surface roughness (as shown inFigure.5). Generally, the substantial number of neurons causes the overfitting and fewer number of neurons responsible for underfitting. A suitable amount of neurons are selected for enhancing the performance of the neural network. Generally, a large number of neurons cause the overfitting and less number of neurons responsible for underfitting. Therefore four different ANN structure was developed by variation of neurons, i.e., 5,10,15, and 20 number of neurons and for these structure R^2, MSE% is calculated using Eq.4,and Average percentage error (APE%)is calculated asdepicted in Table 4.

$$MSE = \frac{1}{n}\sum_{i}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{4}$$

where y_i is the desired Neural Network output, and $\hat{y}_i$ is the neural network output.The assortment of the suitable transfer function is also uniformly significant. The "randperm" function, which returns the data sample in random order, while the order of columns holding milling process surface roughness. Before feeding data to the network, data samples were normalized within a range of 0.1 to 0.9 to equalize the importance of variables." After that, the neural network was developed, conferring the presented parameters in Table 5.

For training of the neural network, 17 samples out of 27 (i.e., 60% of the total sample) are used and 10 samples (i.e., 20%) for validation and 09 samples (i.e., 20%) for test the capability of the trained neural network. The training was accomplished by altering the synaptic weights to diminish the MSE and the weight and bias for the hidden layer shown in Table 6. The regression plot for the ANN structure (Figure.6).The “development of neural network starts with interpreting the data from an excel file, where every testspecified by a grouping of milling factors (Wt.%, N, F, and D) and the subsequent value of surface roughness. After that, randomized the data sample with the help of:

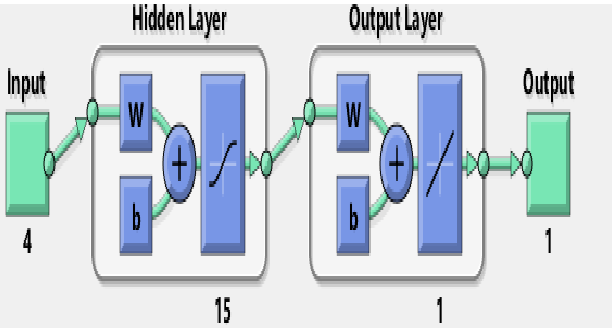

Figure 5. ANN structure (4-15-1)

Table 4. ANN Performances of the proposed networks.

MLP network	R2 (%)	MSE (%)	APE (%)
4-5-1	95.1	7.8	4.08
4-10-1	92.11	3.9	6.08
4-15-1	99.7	2.1	2.08
4-20-1	98.1	4.5	5.08

Table 5: ANN Parameters

Network Type	Feed-forward backpropagation
Transfer function	Hidden layer -Sigmoid Output layer- Linear
Training Algorithm	TRAINLM
Learning Algorithm	LEARNGDM
Data division	Training data-60% Validation data-60% Test data-20%

Table 6. Weights and biases between input and hidden layer

Neuron (j)	Wj1	Wj2	Wj3	Wj4	Bj
1	0.31217	-0.34498	-2.2318	-0.9925	-3.0652
2	1.7984	0.23244	-0.70899	-1.9255	-2.3282
3	1.6092	-1.5216	1.093	-1.3858	-1.6781
4	0.43679	1.2214	0.74388	-2.5858	-1.6221
5	-1.2592	-1.9934	0.12518	1.6079	1.0009
6	2.0492	-1.8611	-0.51232	-0.16767	-0.57506
7	-0.8339	-1.3796	-1.3778	1.9305	0.71615
8	1.4282	-1.1657	0.61017	-2.0719	-0.29933
9	-2.1547	1.1314	0.80839	-0.96541	0.48395
10	0.31719	2.6834	1.0712	-0.73149	1.7771
11	1.301	1.9875	0.39188	-0.31075	-2.0294
12	-1.4005	0.49061	1.2086	1.7069	-0.41595
13	-0.79041	1.6951	0.566	2.2773	-1.6537
14	-1.858	-0.48896	-1.8857	-0.59084	-2.2934
15	-0.80283	-1.568	0.0812	-2.3054	-2.6266

After the training, validation, and testing of the neural network, network simulates with a combination of process parameters and getting predicted value of surface roughness corresponding to simulated experimental run.

Figure. 7 displays the plot between the predicted and experimental value of surface roughness. It was noted that predicted value has a good agreement between experimental value, where a small number of points show the divergence between the two values. It is mainly because of some errors instigated by the measurement and other uncontrollable factors. Still, the pattern of the points can be ignored as the R^2 for training, and testing data surpassed 95%. These outcomes of the milling examinations validate the capability of ANNs to assess the surface roughness during machining of MWCNT polymers with high accuracy.

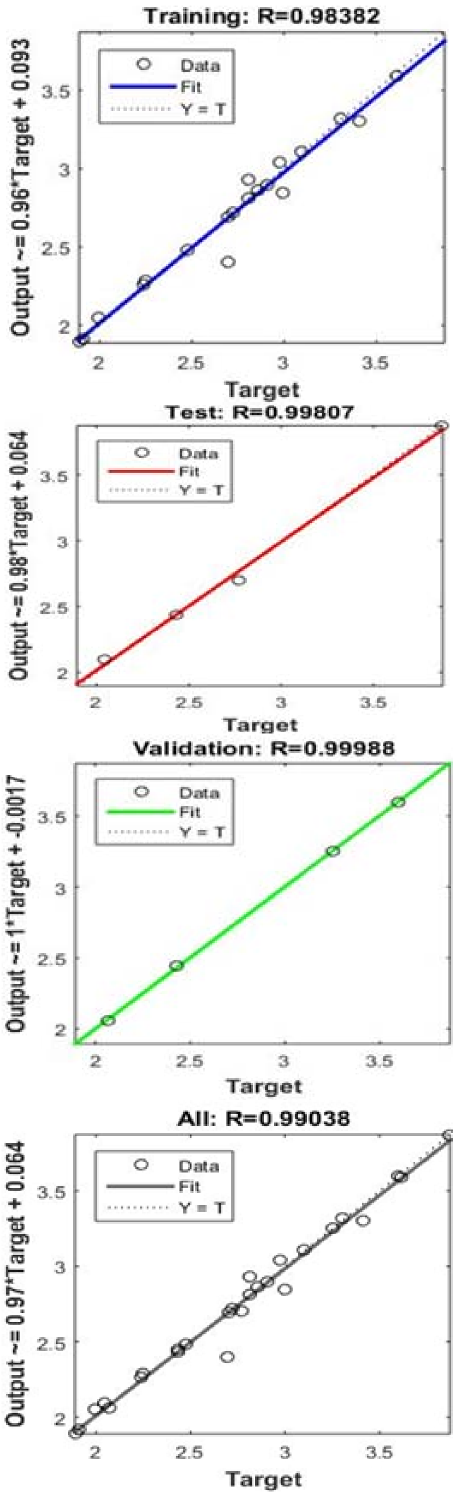

Figure 6.Regression Plot (a)testing (b) test (c) Validation (d) Over all for ANN structure (4-15-1)

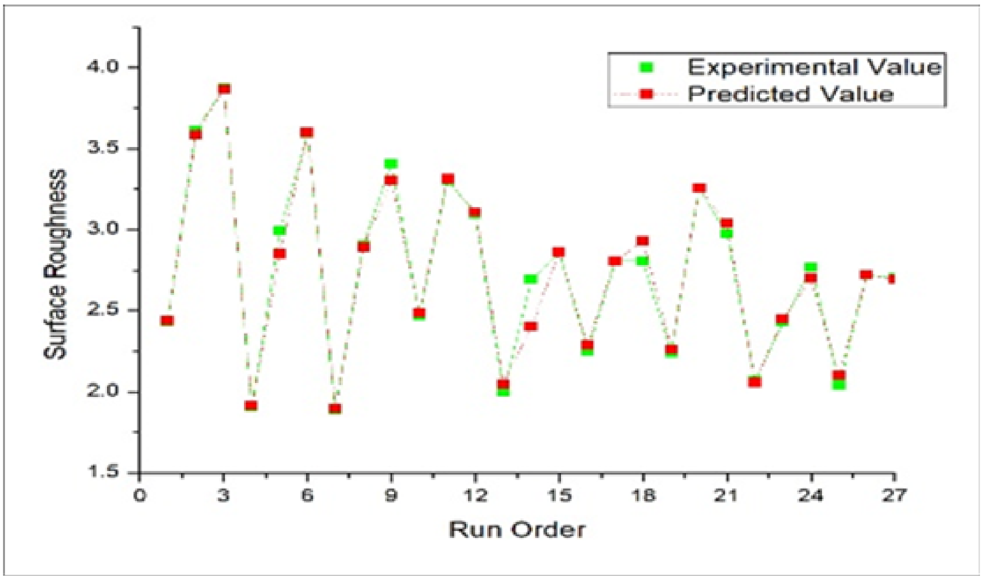

Figure 7. Plot between experimental and predicted value

5. CONCLUSIONS

This manuscript examined the machining behavior of MWCNT/polymer nanocomposites to control the surface roughness of the machined samples. ANN was efficiently utilized for modeling of the surface roughness achieve during milling of MWCNT/epoxy composites. From the ANOVA report, it is observed that that Feed rate (F) is the most significant (55.25%) parameters for surface roughness trailed by Spindle speed (N), MWCNT weight percentage (wt.%) and Depth of cut (D).ANN structure(4-15-1)demonstrates the high yield performance with R2 (%)= 99.7, MSE (%)= 2.1 and APE(%) with 2.08. The selection of suitable algorithm and number of neurons for numbers of the hidden layer is critical parameters for the modeling the complex machining behavior. In the proposed model, the feed-forward back propagation network is used with TRAILM and LEARNGDM training and learning algorithms.The comparison plot between experimental and estimated value for the surface response shows good agreement between them. The desired improvement in surface roughness values with very little error is highly required for a favorable machining environment. Surface finishing is considered as the primary quality indices in the polymer manufacturing sector. Therefore, ANN is a reliable tool to predict and model the machining response. The ability of ANN to model complex and nonlinear behavior of the machining process can gather wide acceptance in manufacturing industries. After training, the functioncan efficiently produce response prediction within limited information. It can be endorsed for quality and productivity control of conventional and non-conventional machining processes.

FUTURE SCOPE OF WORK

The present article deals with the machining of MWCNT reinforced epoxy nanocomposites using biological stimulating neurons system ANN models. The contribution ofother machine factors like different types of tool geometry and tool materials, mechanics of material removal, tooltip temperature in the future can develop a better machining interpretation for proper utilization of proposed novel material in society interest. The ANN models give a satisfactory agreement in outcomes so it can be used in the approximation and prediction of performances of manufacturing procedures such as drilling, turning, diesinking, welding etc. and other complex case studies of industrial engineering.

ACKNOWLEDGMENT

The authors would like to acknowledge the kind support of the Collaborative research scheme of AICTE, New Delhi, India and Uttar Pradesh Council of Science and Technology Lucknow India for extending all possible help in carrying out this research work directly or indirectly.

DECLARATION OF CONFLICTING INTERESTS

The authors declared no potential conflicts of interest.

FUNDING

This experimentation work performed in this article was supported by the Collaborative research scheme of AICTE, New Delhi, India and Uttar Pradesh Council of Science and Technology Lucknow India.

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МОДЕЛИРАЊЕ ПОВРШИНСКЕ ХРАПАВОСТИ НА БАЗИ ВЕШТАЧКЕ НЕУРОНСКЕ МРЕЖЕ КОД ОБРАДЕ ПОЛИМЕРНИХ (ЕПОКСИ) НАНОКОМПОЗИТА ОЈАЧАНИХ ВИШЕЗИДНИМ УГЉЕНИЧНИМ НАНОЦЕВИМА

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Површинска храпавост је у процесу производње најважнији елемент квалитета машински обрађеног производа. Рад се бави моделирањем површинске храпавости коришћењем ANN код обраде полимерног нанокомпозита ојачаног са MWCNT. ANN је развијена као економичан модул за само-учење и флексибилан за променљиве вредности сложених података. Тагучијев план експеримента L27 је савршено искоришћен за поступак обраде. Параметри обраде: MWCNT (теж.%), брзина вретена, брзина помоћног кретања и дубина резања су анализирани да би се добила минимална површинска храпавост обрађених узорака. ANOVA анализа је показала да су за храпавост најважнији параметри брзине помоћног кретања (55,25%), затим брзине вретена, тежинског процента MWCNT и дубине резања. Мрежа пропагације унапред и уназад је коришћена за ANN модел са функцијама TRAINLM и LEARNGDM које се користе као алгоритам за тренинг и учење. Избор адекватног модела је извршен на бази коефицијента корелације (R^2), средње квадратне грешке (MSE) и просечне процентне грешке (APE). Добијени модел има велику прецизност: R^2 > 99%, MSE < 0,2%, APE < 3%. Приказана експериментална и предвиђена вредност показују да је модел адекватан и применљив за услове машинске обраде.