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

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 minimal Ra 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 synergic 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 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 nanocarbon family is a single-wall carbon nanotube (SWCNT), MWCNT, carbon 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 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 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
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 by pioneer researchers. 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].

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 opening stage, work is not satisfactorily prospered 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 layout milling experimentation. An attempt has been made to inves-
igate 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 by the 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.% Wt. %          | Wt.   | 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 more than one hidden layer. Input layer neurons handover the input variables $X_i$ $(i=1,2, 3...n)$ 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, resolve by the connection and synaptic weights among neurons.

The additional function characterized assembly of an artificial neuron $(j)$, which sumps inputs $X_i$ after weighting them with the corresponding weights $W_{ij}$ from the input layer. The weighted sum $S_j$ given as Eq.1

$$S_j = \sum_{i=1}^{n} w_{ij}x_i$$  \hspace{1cm} (1)

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

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

The function $f$ can also be called “Transfer function.” The commonly used is the sigmoid function as follows

$$f(x) = \frac{1}{1 + \exp(-x)}$$  \hspace{1cm} (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 effectivity done to identify the prominent factor. From Table 3, it was noticed 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 $(D)$.

| Source | DF | Seq SS | Adj SS | Adj MS | F-Value | P-Value |
|--------|----|--------|--------|--------|---------|---------|
| Regression | 11 | 7.52888 | 7.52888 | 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 | 0.137 |
| 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 in Figure.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 as depicted in Table 4.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$  \hspace{1cm} (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 testing.
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 test specified 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)](image)

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      | 92.1   | 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  | -0.70899| -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 | 1.3134  | 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 R² 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)
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 achieved during milling of MWCNT/epoxy composites. From the ANOVA report, it is observed that feed rate (F) is the most significant (55.25%) parameter 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 $R^2(\%) = 99.7$, 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 modeling the complex machining behavior. In the proposed model, the feed-forward back propagation network is used with TRAILM and LEARNNGDM 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 function can 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 of other 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.

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DECLARATION OF CONFLICTING INTERESTS

The authors declared no potential conflicts of interest.

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МОДЕЛИРАЊЕ ПОВРШИНСКЕ ХРАПАВОСТИ НА БАЗИ ВЕШТАЧКА НЕУРОНСКЕ МРЕЖЕ КОД ОБРАДЕ ПОЛИМЕРИХ (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 са вршимо искоришћен за поступак обраде. Параметри обраде: MWCNT (тежински проценат), 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 LEARNNGDМ које се користе као алгоритам за тренинг и учење. Избор адекватног модела је извршен на бази коефицијента корелације (R²), средње квадратне грешке (MSE) и просечне процентне грешке (APE). Добијени модел има велику прецизност: R² > 99%, MSE < 0,2%, APE < 3%. Приказана експериментална и предвиђена вредност показују да је модел адекватан и применљив за услове машинске обраде.