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Evaluation of Surface Roughness of Carbon Nanotube TMT Nanosteel Material Using Taguchi Analysis and Neural Networks

S. Prabhu†*, & B. K. Vinayagam‡

†Department of Mechanical Engineering, SRM University, Chennai, India, *Email: prabhume@yahoo.Co.in
‡Department of Mechatronics Engineering, SRM University, Chennai, India

ABSTRACT: Neural network analysis is used to predict the surface roughness in CNC lathe machining process of Thermo Mechanically Treated (TMT) steel. L9 orthogonal array was used to optimize the machining parameters using Taguchi design of experiment technique. The data used for the training and checking of the networks performance derived from experiments conducted. Analysis of Variance (ANOVA) and F-test were used to determine the significant parameter influencing the output parameters of surface roughness. The statistical analysis implies that the cutting speed was an utmost parameter on surface roughness. TMT nanosteel are tested using XRD analysis to obtain voids structure of nanosteel. Using the feed forward Artificial Neural Networks (ANNs) the experimental values are trained with the Levenberg-Marquardt algorithm is used the most influential factors were determined. ANN based predicted the surface roughness with a mean squared error is 2.90% for with CNT nanosteel.

KEYWORDS: Nanosteel; Surface roughness; Taguchi analysis; ANOVA; Neural network.

INTRODUCTION

Nano composites are differing from conventional composite materials due to the exceptionally high surface area to volume ratio of the reinforcing phase. The large amount of reinforcement surface area means that a relatively small amount of nanoscale reinforcement can have an observable effect on the macro scale properties of the steel. Nanocomposites with special matrices and filler materials may achieve significant and simultaneous improvements in stiffness, fracture toughness, impact energy absorption and vibration damping and these characteristics could be of particular importance in automobile or airplane structures (Lingyu Sun, et al., [1]). Carbon Nano Tubes (CNT) is one of the most exciting nanostructural materials with their excellent mechanical properties like high strength to low weight ratio, high young's modulus of 1 Tpa and low density of 2.0 g/cm^3 makes them as a viable reinforcing phase in a variety of polymer, ceramic, and metallic matrices to design high-performance nano composite materials. Surface quality is an essential consumer requirement in machining processes because of its impact on product performance. The characteristics of machined surfaces have significant influence on the ability of the material to withstand stresses, temperature, friction and corrosion.

Previous Work

Ulas Caydas and Ahmet Hascalık [2] proposed artificial neural network (ANN) and regression model were developed to predict surface roughness in abrasive water jet machining (AWJ) process. In the development of predictive models, machining parameters of traverse speed, water jet pressure, standoff distance, abrasive grit size and abrasive flow rate were considered as model variables. For this purpose, Taguchi's design of experiments was carried out in order to collect surface roughness values. Tsao and Hocheng [3] presents the prediction and evaluation of thrust force and surface roughness in drilling of composite material using candle stick drill. The approach is based on Taguchi method and the artificial neural network. The experimental results indicate that the feed rate and the drill diameter are the most significant factors affecting the thrust force, while the feed rate and spindle speed contribute the most to the surface roughness.

Ko, et al., [4] proposed the artificial neural network (ANN) using Taguchi method has been implemented for minimizing objective functions relevant to the forming process. The orthogonal array and the results of simulation are used as training data of ANN. Benardos and Vosniakos [5] developed a neural network modeling approach is presented for the prediction of surface roughness (Ra) in CNC face milling. The data used for the training and checking of the networks performance derived from experiments conducted on a CNC milling machine according to the principles of Taguchi design of experiments method. Using feed forward artificial neural networks (ANNs) trained with the Levenberg-Marquardt algorithm, the most influential of the factors were determined. Mirigul Altan [6]

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developed the optimal injection molding conditions for minimum shrinkage was determined by the Taguchi, experimental design and the analysis of variance (ANOVA) methods. After the degree of significance of the studied process parameters was determined, the neural network (NN) model was generated and was shown to be an efficient predictive tool for shrinkage.

Ihsan Korkut, et al., [7] developed the tool–chip interface temperature results obtained from mathematical equations with Regression Analysis (RA) and Artificial Neural Network (ANN) model and the experimental results available in the literature obtained by using AISI 1117 steel work piece with embedded K type thermocouple into the uncoated cutting tool are compared. The training ANN model with the Levenberg-Marquardt (LM) algorithm provides more accurate prediction and is quite useful in the calculation of tool–chip interface temperature when compared with the trained RA method in machining. John, et al., [8] describes an innovative application of the Taguchi method for the determination of these parameters to meet the training speed and accuracy requirements. Using the Taguchi method, both the micro-structural and macro-structural aspects of the neural network design parameters can be considered concurrently. The feasibility of using this approach is demonstrated in this paper by optimizing the design parameters of a back-propagation neural network for determining operational policies for a manufacturing system. Lung Kwang Pan, et al., [9] presents and demonstrates the effectiveness of optimizing multiple quality characteristics of laser welded titanium alloy plates via Taguchi method-based Grey analysis. The modified algorithm adopted here was successfully used for both detraining the optimum settings of machine parameters and for combining multiple quality characteristics into one integrated numerical value called Grey relational grade.

Durmus Karayel [10] proposed a neural network approach is presented for the prediction and control of surface roughness in a computer numerically controlled (CNC) lathe. Experiments have been performed on the CNC lathe to obtain the data used for the training and testing of a neural network. A feed forward multilayered neural network was developed and the network model was trained using the scaled conjugate gradient algorithm (SCGA), which is a type of back-propagation. Fabrício Jose Pontes, et al., [11-13] presents a study on the applicability of radial base function (RBF) neural networks for prediction of Roughness Average (Ra) in the turning process of SAE 52100 hardened steel, with the use of Taguchi's orthogonal arrays as a tool to design parameters of the network. Experiments were conducted with training sets of different sizes to make possible to compare the performance of the best network obtained from each experiment. Artificial neural networks (ANN) models obtained proved capable to predict surface roughness inaccurate, precise and affordable way.

Ying Sun, et al., [14] developed a CNT reinforced nickel nanocomposites fabricated with an innovative electrochemical co-deposition process for achieving good interfacial bonding between CNT and metallic matrices. You, et al, [15] proposed to use nano structures directly to fully utilize the nice mechanical and thermal properties for nano machining. CNT's were directly used as cutting grains. For the CNT grains, used epoxy as one of the bonding materials and a series of CNT grinding wheels were fabricated to demonstrate the effectiveness of the proposed new type of abrasive tool. The CNT wheels are made of 1% MWCNTs or Multi Wall CNTs. Carbon nanotubes can be used as cutting grains for nano machining. Yan-Cheering Linn, et al., [16] developed the force assisted standard EDM machine. The effects of magnetic force on EDM machining characteristics were explored. Moreover, this work adopted an L18 orthogonal array based on Taguchi method to conduct a series of experiments, and statistically evaluated the experimental data by analysis of variance (ANOVA).

In the present work, a modest attempt have been made to dispersion of Multi wall carbon nanotubes (MWCNT) into Thermo Mechanically Treated(TMT) steel materials and machining was carried out using L9 orthogonal Taguchi design of experimental techniques in CNC lathe process. Using feed forward Artificial Neural Networks (ANNs) trained the experimental values with the Levenberg-Marquardt algorithm, the most influential of the factors were determined. In this study, multiwall carbon nano tubes are used as a composite nano material with TMT steel. The sources of carbon nano tubes are received from Cheap tubes Inc., USA [www.cheaptubes.com]. The specification of multi wall carbon nano tubes are given in Table 1.The nanotubes had an average diameter of 10-20 nm and a length of 10-30 micrometers, and were produced catalytically from hydrocarbon materials on nanocatalysts under high pressure. Multiwall carbon nano tubes were mixed with TMT steel using stir casting techniques. Figure 1 shows a Transmission Electron Microscopy (TEM) image of the multiple wall carbon nano tubes.

CNTs having a tremendously high surface area and good electrical conductivity. The CNT is 100 times stronger than steel (Mamalis, et al., [17]) and weight is 1/6th weight of steel. CNT having high strength to weight ratio used in aerospace industry. Young's modulus of CNT's is over 1 TPa vs 70 GPa for aluminum, steel 200 Gpa and 700 GPa for C-fibre. The strength to weight ratio is 500 times greater than aluminum and maximum strain will be 10% much higher than any material. Thermal conductivity of CNT is 3,320 W/mK in the axial direction with small values in the radial direction. Electrical conductivity of CNTs is 109 A/cm^2 and copper is 106 A/cm^2. CNTs having very high current carrying capacity, excellent field emitter and high aspect ratio.

Table 1. Specification of MWCNT's.

OD	10 to 20 nm
Length	10 to 30 µm
Purity	> 95 wt%
Ash	< 1.5 wt%
Specific Surface Area	> 233 m^2/g
Electrical Conductivity	> 10^{-2} S/cm

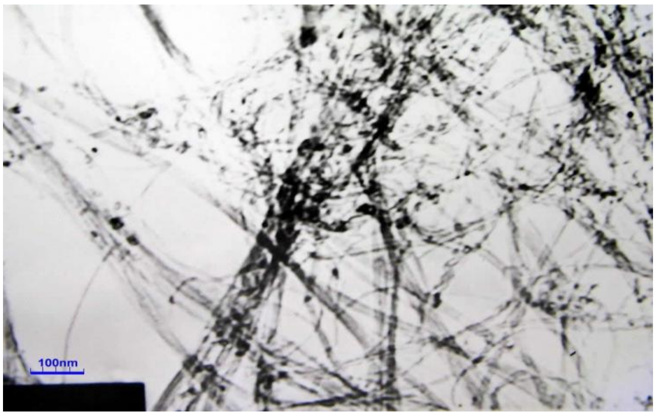

Figure 1. TEM image of MWNT's 95wt% < 8nm OD.

TMT Steel

Thermo Mechanically Treated (TMT) steel, can be described as a new-generation-high-strength steel were introduced in India during 1980-1985 and having superior properties such as weld ability, strength, ductility and tensility, which meet the highest international quality standards. Thermo mechanical treatment is an advanced heat treatment process in which hot bars coming out of last rolling mill stand are rapidly quenched through a series of water jets. Rapid quenching provides intensive cooling of surface resulting in the bars having hardened surface with hot core. The rebars are then allowed to cool in ambient conditions. During the course of such slow cooling, the heat released from core tempers the hardened surface while core is turned in to ferrite-pearlite aggregate composition. The TMT process gives the bar superior strength and anti-corrosive properties. The soft ferrite-pearlite core enables the bar to bear dynamic and seismic loading. TMT bars are most preferred because of their flexible nature. They have fine welding features. External ribs running across the entire length of the TMT bar give superior bonding strength between the bar and the concrete. A high tensile strength and better elongation value gives you great savings

Table 2 lists the chemical composition (wt%) of the TMT steel was tested in Pulkit Metals Pvt ltd, Puduchery, India according to OES-CML/WP/35 & IS 1586-2000 standards.

From the Table 2, the addition of carbon nano tubes into steel which (in Table 2) shows that the carbon, silicon, Manganese and Chromium content is increased. Phosphorus and sulpher content are decreased. Higher carbon contributes to the tensile strength of steel, that is, higher load bearing capacity and vice versa. Higher manganese content in steel increases the tensile strength and also the carbon equivalent property. Presence of higher impurity in sulphur makes the bar brittle during twisting. Presence of lower phosphorous leads to brittleness is decreased and make the steel little flexible. Present Chromium (Cr) as an impurity from the scrap and influences carbon equivalent and increases corrosion resistance property. Ceq property is required to set the cooling parameters in TMT process and a slight variation in carbon equivalent may alter the physical properties. In case of TMT bars, carbon equivalent has a maximum limit of 0.42 percent but there is no lower limit prescribed. As such, as long as the chemical composition and physical properties of raw materials are within specified limits, the variation in carbon equivalent as in the case of TMT bars.

The hardness values of TMT steel Fe415 grade was obtained according to IS 1586-2000 [RA2010] standards at Kidao Lab, Chennai and the hardness is decreased from 97.6 to 96.8 HRB. Now mixing the 0.5 wt% of Multi wall carbon nano tube with TMT steel and then hardness is found that 78.8 HRB which is very well decreased. The reason for that the CNT is penetrated the interstitial atoms with steel because of diameter of CNT is few nanometer and length is few micro meter. The CNT is having very good young's modulus of 1 TPa which leads to parent material getting soft and flexible as well as strength is increased.

Table 2. Chemical Composition of the TMT steel [wt%] with CNT.

Element (Wt%)	0wt% CNTs	0.5wt% CNTs
C	0.178	0.215
Si	0.176	0.188
Mn	0.630	0.690
P	0.05	0.028
S	0.036	0.032
Cr	0.18	0.223
Ni	0.101	0.265
Mo	0.044	0.053
Al	0.0042	0.0044
Cu	0.223	0.302
Zn	0.013	0.017
Co	0.012	0.019
Ti	0.003	0.001
V	0.001	0.0016
Ceq	0.349	0
Cre	0.403	0
Nb	0.003	0.004
W	0.03	0.024
Pb	0.006	0.018
Sn	0.024	0.016
As	0.0078	0.017

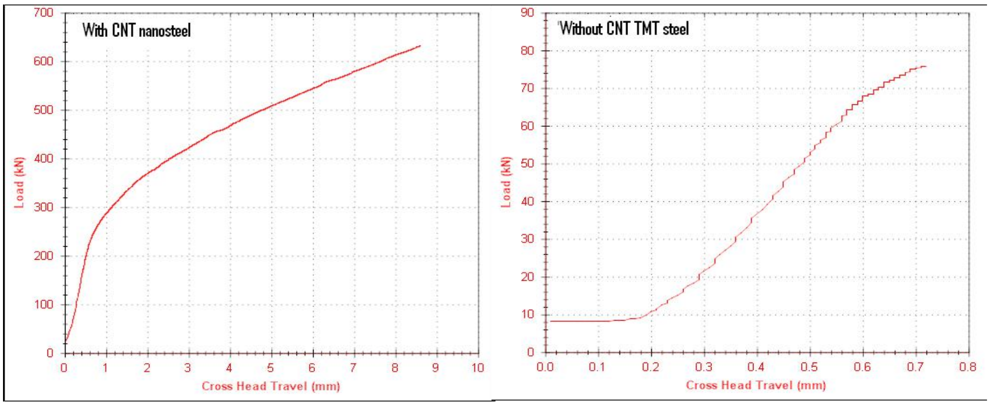

Figure 2. Compressive strength for with CNT (left) and without CNT (Right) for TMT Nano steel.

The strength of the nanosteel is tested using servo controlled compressive testing machine, in Hi-tech equipment ltd, Chennai. The machine has a maximum load carrying capacity of 100 tones. Typical stress strain curve of monotonically loaded (compression) CNT nanosteel rebar is shown in Figure 2 (left). The curves exhibit an initial elastic portion, a yield plateau (that is, a yield point beyond which the strain increases with increase in stress), a strain hardening range in which stress again increases with strain, and finally a range in which the stress drops off until fracture occurs. The slope of the linear elastic portion of the curve represents the modulus of elasticity of steel. The stress at the yield point, referred as the yield strength, is a very important property of steel reinforcement. Reinforcement is generally characterized by its yield strength. The maximum compressive strength of nano steel with CNT is 522 N/mm^2 over a cross head travel of 8.5 mm and for without CNT TMT steel the strength is 424 N/mm2.

The results show that compression strength of the nanosteel is increased 18% stronger than ordinary TMT steel.

XRD Analysis

X-ray Diffraction (XRD) used to measure the average spacing's between layers or rows of atoms. It determines the orientation of a single crystal or grains of steel material with CNT is analyzed and find the crystal structure of an unknown material and measure the size, shape and internal stress of small crystalline regions.

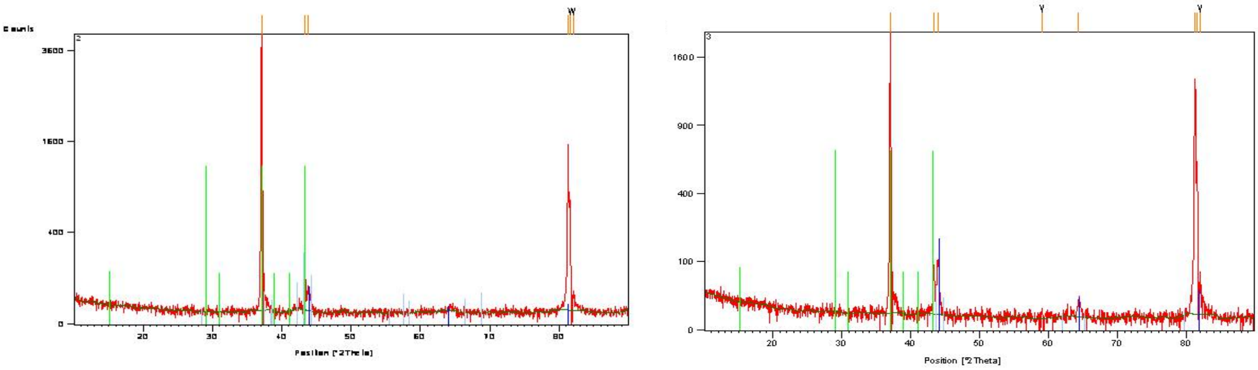

Figure 3. X-ray measurement of nanocomposite for 0 wt% CNT (left) and 3 wt% CNT with TMT steel (Right).

Figure 3 shows that the peak height is about 3620 counts and the peak angle lays at 38° and d spacing of 2.3376 for without CNT and for nanosteel 1630 counts and the peak angle lays at 37° and d spacing of 2.33423. By comparing the peak value shown in Table 3, for the samples know that the penetration of the x-rays decreases with the addition of carbon nano tube. This shows that the nos. of voids and cracks reduce with the addition of carbon nano tube in the samples. Because of filling the carbon nano tube with voids of Steel the hardness is decreased and the same time strength is increased. So TMT steel nano composites developed to increase high strength to low weight ratio.

Table 3. Peak position and d-spacing of with and without CNT TMT steel nanocomposite.

Samples	Peak height (Cts)	d-Spacing [Å]	Hardness (HRB)	Displacement [2Th.]
0 wt% CNT with TMT steel	3620	2.33760	96.8	0.105
3 wt% CNT with TMT steel	1630	2.33423	78.8	0.138

PROPOSED METHODOLOGY

Uniturn 300 model CNC lathe Machine is used to machine the TMT with carbon nano tube steel nanocomposite material. Taguchi design of experiments technique permits us to carry out the modeling and analysis of the influence of process variables (design factors) on the response variables. In the present study, the depth of cut (d, mm), spindle speed (N, rpm) and feed rate (f, mm/min) have been selected as design factors. The process variables with their values on different levels are listed in Table 4. The selection of the values of the variables is limited by the capacity of the machine used in the experimentation as well as the recommended specifications for TMT nano steel work piece and CNT combinations. Three levels within the operating range of the parameters have been selected for each of the factors.

TMT steel is mixed with 0.5 wt% of multi wall carbon nano tube by stir casting technique and the nanosteel is fabricated. The nanocomposite hardness is tested using RAB250 hardness tester model. The 100 kg load is applied through 1/16 inch diameter of ball indenter is used to obtained the hardness of the nanosteel and adding a CNT the hardness is decreased due to high young's modulus 1 TPa of CNT. The XRD analyses are done on nanosteel to understand the voids structure of TMT nanosteel. This paper presents the development of a neural network model using feed forward network. The goal was to train an artificial neural network to include the most important factors affecting surface roughness in order to make accurate and consistent predictions. The data needed for the training must derive from experimental values.

RESULTS AND DISCUSSIONS

The studies of process parameters which influence the objective function and which parameters will impact largely to this surface finish is analyzed. The parameters control factors and their levels are identified in Table 4. In this optimization, three levels and three parameters are taken based on L9 orthogonal array in Taguchi design of experiments. The surface roughness with and without CNT TMT nanosteel and signal noise ratio (S/N) values are tabulated in Table 5. The objective function of this method is to improve the surface finish of the TMT nanosteel work piece which is used in rods and earth quake resistance material. If the calculated S/N ratio is too small that indicates the level of perfection of the experiments. The formula used for calculating the S/N ratio is given below:

$$\frac{\text{S}}{\text{N}}\text{Ratio}(\eta) = -10\log 10\frac{1}{\text{n}}\sum_{i=1}^{\text{n}} \text{y}^2 \tag{1}$$

n= no. of experiments, y = no. of response value

Table 4. Identifying control factors and their levels.

Item	Control Factor	Units	Level 1	Level 2	Level 3
A	Cutting Speed	Rpm	500	1000	1500
B	Feed	mm/min	50	100	150
C	Depth of cut	mm	0.5	0.75	1.0

Table 5. Surface roughness and S/N ratio value.

Exp. Nos.	Coded Values			Actual Values			Without carbon nano tubes Surface roughness (Ra) (y) µm	With carbon nano tubes Surface roughness (Ra) (y) µm	S/N ratio Without nano tubes	S/N ratio With nano tubes
	A	B	C	A	B	C				
1	1	1	1	500	50	0.5	1.31	0.70	-2.345	3.098
2	1	2	2	500	100	0.75	3.40	3.61	-10.629	-11.150
3	1	3	3	500	150	1.0	1.20	1.72	-1.583	-4.710
4	2	1	2	1000	50	0.75	2.05	1.09	-6.235	-0.748
5	2	2	3	1000	100	1.0	2.33	0.43	-7.347	7.330
6	2	3	1	1000	150	0.5	2.32	1.56	-7.309	-3.862
7	3	1	3	1500	50	1.0	3.75	0.49	-11.480	6.196
8	3	2	1	1500	100	0.5	3.74	0.54	-11.457	5.352
9	3	3	2	1500	150	0.75	2.75	0.71	-8.786	2.974
					Mean				-7.463	0.497

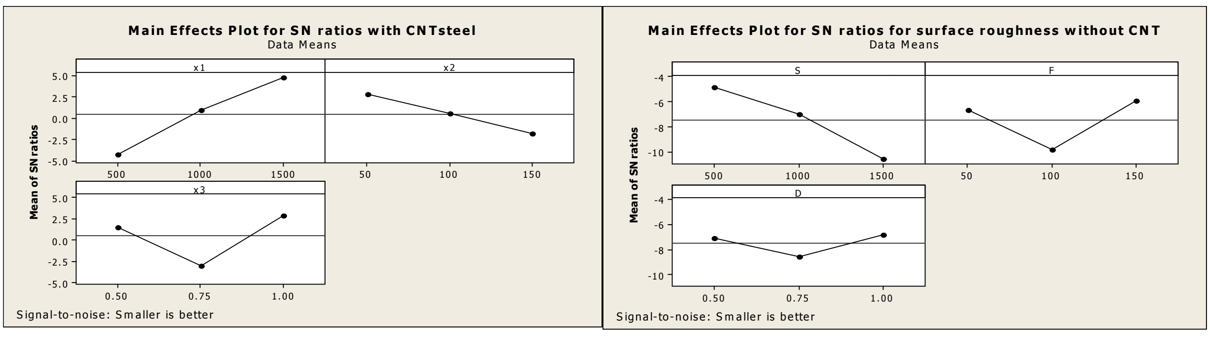

Figure 4. Factor effect diagram for S/N Ratio of with CNT steel (left) and without CNT steel (Right).

The Level 3 of A and Level 1 of B and level 3 of C give the maximum effect of improving surface roughness which shows in Figure 4 (left). Interestingly A3, B1 and C3 is the best combination for cutting speed 1500 rpm, feed 50 mm/min and depth of cut 1mm gives optimum results and influence the surface finish more for with CNT nanosteel materials. Level 1 of A and Level 3 of B and level 3 of C in Figure 4 (Right) gives the maximum effect of improving Surface roughness for without CNT nanosteel.

The predicted S/N ratio ή using the optimal levels of the parameters can be calculated as:

$$ή = \eta_m + \sum_{i=1}^{p} \eta_i - \eta_m \quad (2)$$

η_m – Total mean of S/N ratio, η_i- mean of S/N ratio at the optimum level and p is the number of main parameters that significantly affect the performance.

For without CNT nanosteel, the predicted surface roughness (Ra) is 1.55 µm and actual surface roughness (Ra) is 1.20 µm. For CNT nanosteel, the predicted surface roughness (Ra) is 0.618 µm and actual surface roughness (Ra) is 0.49 µm (Figure 5). In surface finish analysis, the main variables are cutting speed and depth of cut, among these three parameters in optimization technique cutting speed is ranked one for both the cases which influences the surface finish characteristics (Table 6-7).

Table 6. Determining the factor effects of S/N ratio without CNT nanosteel for surface roughness.

Factor	Level 1	Level 2	Level 3	Delta	Rank
A-Cutting speed	-4.853	-6.964	-10.575	5.722	1
B-Feed	-6.687	-9.811	-5.893	3.918	2
C-Depth of cut	-7.038	-8.550	-6.804	1.747	3

Table 7. Determining the factor effects of S/N ratio with CNT nanosteel for surface roughness.

Factor	Level 1	Level 2	Level 3	Delta	Rank
A-Cutting speed	-4.2542	0.9065	4.8410	9.0952	1
B-feed	2.8485	0.5109	-1.8661	4.7146	3
C-depth of cut	1.5292	-2.9746	2.9387	5.9133	2

Confirmation Test

The confirmation experiment is the final step in the first iteration of the design of experiment process. The purpose of the confirmation experiment is to validate the conclusions drawn during the analysis phase. The confirmation experiments were conducted by setting the process parameters at optimum level. Cutting speed 1500 rpm and feed 100 mm/min and depth of cut 0.75mm as optimum parameters and the actual surface roughness was obtained without carbon nano tubes is 1.20 µm compared to predicted surface roughness 1.55 µm. Similar way with CNT steel of cutting speed of 1500 rpm, feed 50 mm/ min and depth of cut 0.1mm as optimum parameters and the actual surface roughness was obtained with carbon nano tubes 0.49 µm compared to predicted surface roughness 0.618 µm.

ANOVA Analysis

The purpose of analysis of variance is to find the significant factors affecting the surface roughness in CNC Lathe process to improve the surface finish of the CNT TMT nanosteel work piece. ANOVA analysis gives clearly how the parameters affect the response and the level of significance of the factors. In this study, the three main parameters considered are cutting speed, feed and depth of cut. The ANOVA analysis clearly indicates that the R2 value 80.06% for TMT nanosteel is higher than without CNT nanosteel (75.75%). The high R2 value indicates that better the model fits with experimental data. Here 0.334 p value of cutting speed is significant. The main output from an analysis of variance study ANOVA arranged in a table 8 and 9. Larger FAo value (1.99) indicates that the variation of the process parameter make a significant changes on the surface roughness.

Neural Network

For modeling the lathe machining processes the Neural Network (NN) is attempt to predict the surface roughness values for with and without using TMT nanosteel. NNs are well suited for problems whose solutions require knowledge that is difficult to specify but for which there are enough data or observations.

Neural networks are basically connectionist systems in which various nodes are interconnected shown in Figure 5. A typical neuron receives more than one input signal. Here cutting speed, feed and depth of cut is given as an input signal and surface roughness is given as an output signal from experimental data. After choosing the network architecture the network is trained. The network performs the adjustment of its parameters so that error between the actual experimental values and desired output is minimized. The feed forward back propagation neural network is most widely used as a neural network. The back propagation algorithm iteratively adjusts the network weights to minimize the squares objective function, the sum of the squared residuals (Difference between the desired and estimated output). The weights Wn are adjusted by a multiple linear regression procedure so that sum of the squared residuals is minimal.

Table 8. ANOVA analysis for the surface roughness without CNT based TMT Nanosteel.

Machining parameters	Degree of Freedom (f)	Sum of Squares(SSa)	Variance(Va)	FAo	P	Contribution (%)
A	2	3.211	1.606	1.30	0.435*	38.95
B	2	0.951	0.476	0.39	0.722	11.53
C	2	1.612	0.806	0.65	0.605	19.55
Error	2	2.468	1.234			29.99
Total	8	8.243				100

*Significant

S = 0.942715 R-Sq = 75.75% R-Sq(adj) = 72.99%

Table 9. ANOVA analysis for the surface roughness with CNT based TMT Nanosteel.

Machining parameters	Degree of Freedom (f)	Sum of Squares(SS_A)	Variance(V_A)	FA_o	P	Contribution (%)
A	2	3.5450	1.7725	1.99	0.334*	48.42
B	2	1.8350	0.9175	1.03	0.492	25.00
C	2	0.1715	0.0857	0.10	0.912	2.42
Error	2	1.7774	0.8887			24.2
Total	8	7.3289				100

*Significant

S = 1.11077 R-Sq = 80.06% R-Sq(adj) = 76.04%

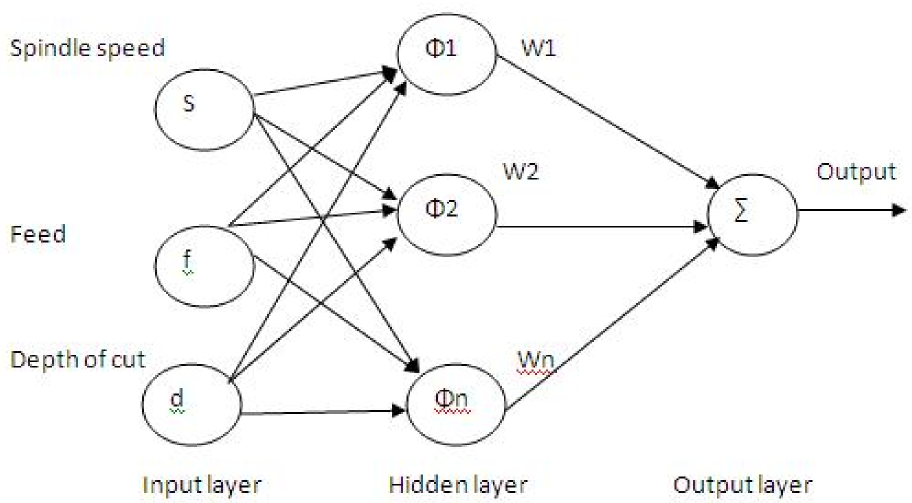

Figure 5. Neural network architecture.

Levenberg-Marquardt (trainlm) training method has been used shown in Figure 6 with the mean square error performance function with random data division. The magnitude of the gradient 0.000401 and the number of validation checks 6 are used to terminate the training. The gradient will become very small as the training reaches a minimum of the performance. Here the magnitude of the gradient is 1e-10 is less than 1e-5 then the training will stop. The number of validation checks represents the number of successive iterations that the validation performance fails to decrease. If this number reaches default value of 6 then the training will stop. In almost 95% of the training cases early stopping would occur while not more than 10 or 20 epochs were required in the majority of the training cases.

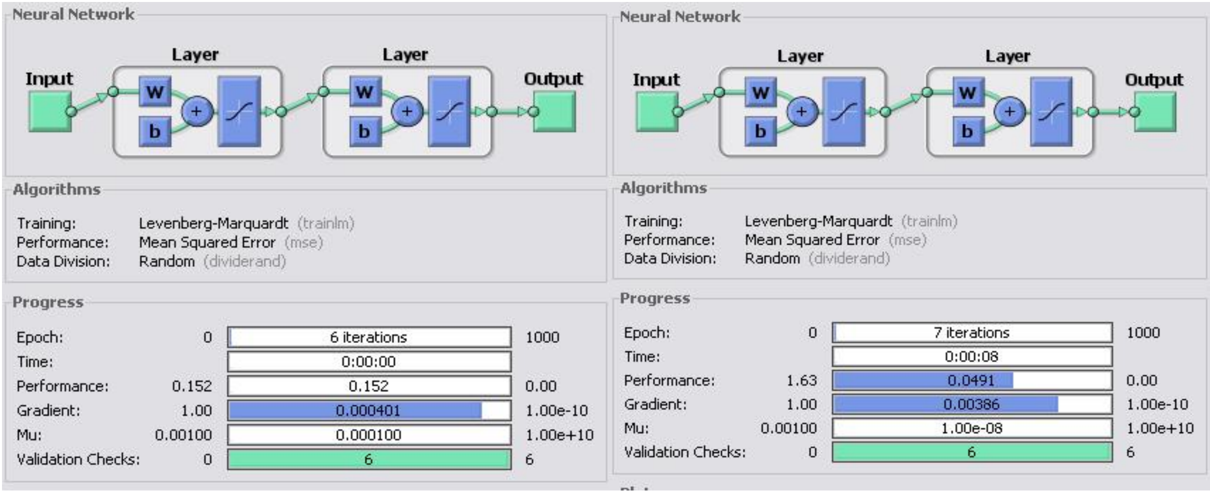

Figure 6. Neural network progress for without CNT steel (Left) and with CNT steel (Right).

From the training window can access three plots like performance, training state and regression. The performance plot shows the value of the performance function versus the iteration number. It plots training, validation and test performances as shown in Figure7. The Mean square error (MSE) values in y axis and number of epochs in x axis. The best validation performance is 0.39925 at epoch 2 for without CNT and for with nanosteel 0.029 at epoch 1. At the iteration 2 validation and testing values are converging and then trained values are decreased rapidly for without CNT steel.

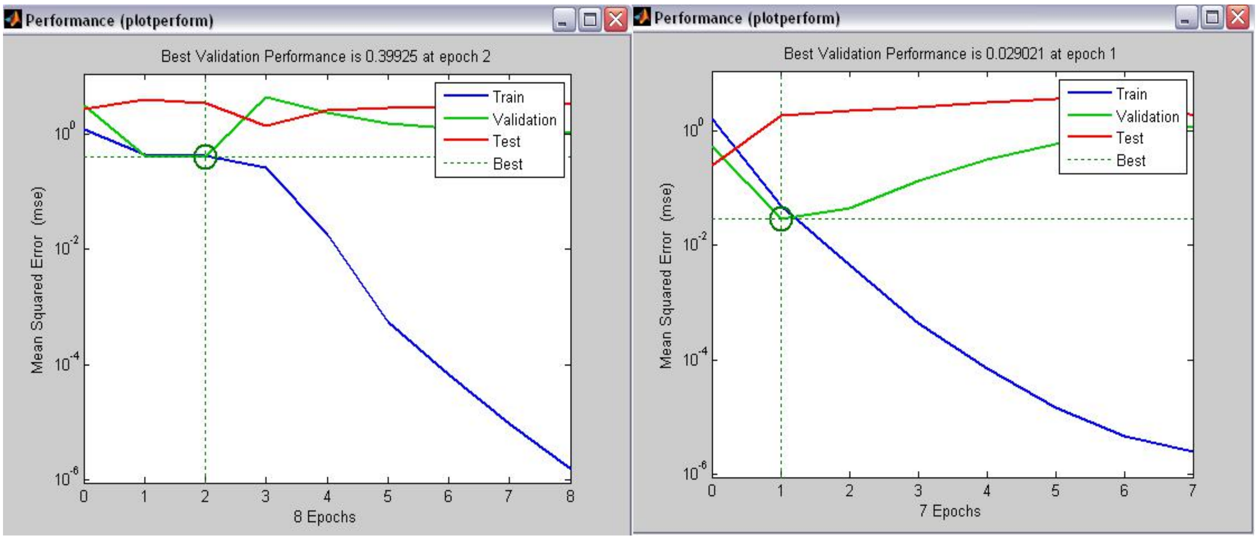

Figure 7. Training window for performance plot for without CNT steel (left) and with CNT steel (Right).

The iteration at which the validation performance reached a minimum was 2 and the training continued for 6 more iteration before the training stopped. The validation and test curves are very similar.

The training state plot shows the progress of other training variables, such as the gradient magnitude, the number of validation checks, etc. Here from the Figure 8 without CNT nanosteel the gradient values of 0.00040126 and Mu value of 0.0001 and validation check 6 at epochs of 6 and for with CNT nanosteel the gradient values of 0.0039624 and Mu values of 1e-007 and validation check 6 at epoch of 6.

The next step in validating the network is to create a regression plot, which shows in Figure 9 the relationship between the outputs of the network and the targets. If the training were perfect, the network outputs and the targets would be exactly equal, but the relationship is rarely perfect in practice. Use the regression plots to validate network performance as called in Post-Training Analysis. The four axes represent the training, validation, testing data and over all data. The dashed line in each axis represents the perfect result – outputs = targets. The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets.

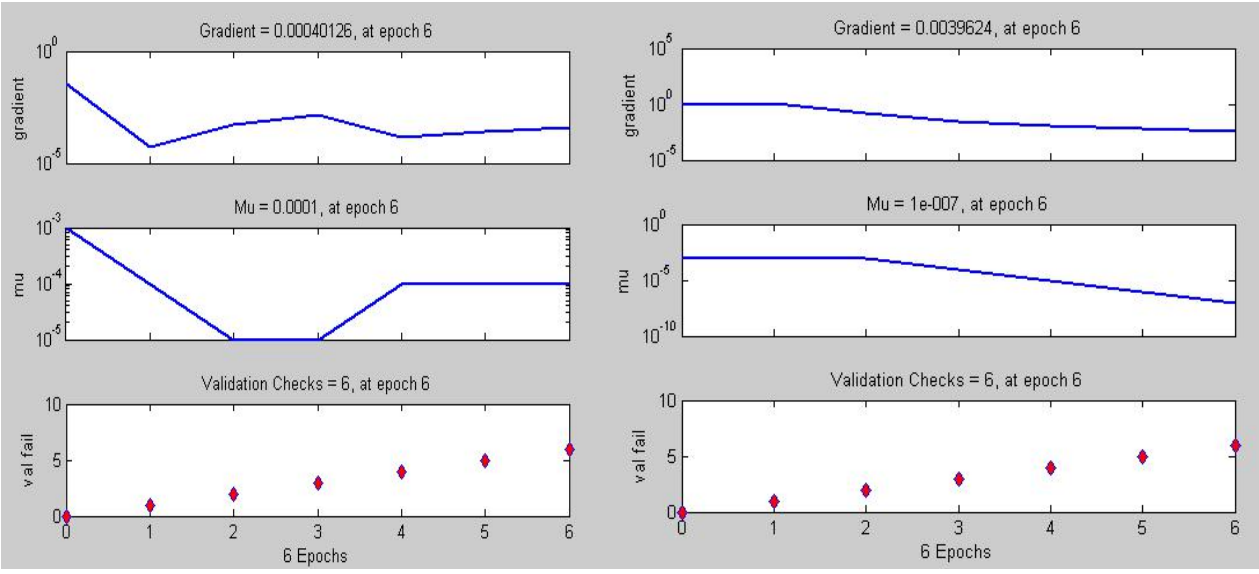

Figure 8. Training state plot for without CNT steel (left) and with CNT steel (Right).

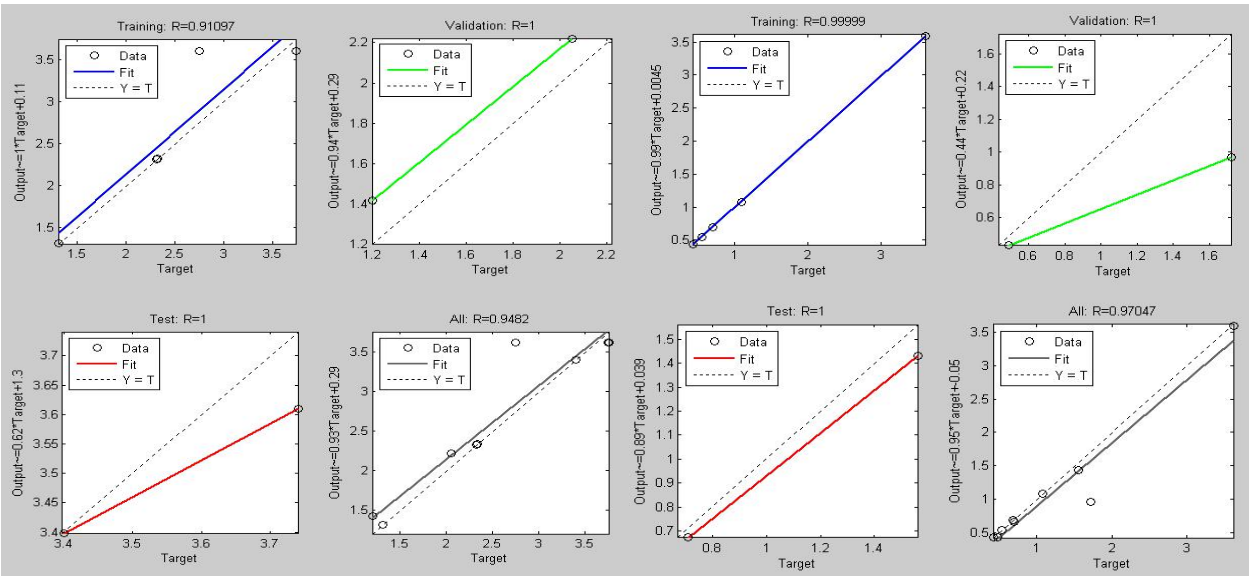

Figure 9. Regression plot between network output and target for without CNT steel (left) and with CNT steel (Right).

In the regression analysis the training data is fit with output and R values shows that 0.9107 and for with CNT 0.999. The high R value near to 1 is indicated that better training model fit well with output data and the validation and testing the R values are 1. The overall performance of training, testing and validation the R value is 0.9482 and for with CNT nanosteel 0.97047 which means that less trained error with good output values fit very well with model. The scatter plot is helpful in showing that certain data points have poor fits. There is a data point in the overall set whose network output is close to 3.5, while the corresponding target value is about 2.70. The next step would be to investigate this data point to determine if it represents extrapolation (i.e., is it outside of the training data set). If so, then it should be included in the training set, and additional data should be collected to be used in the test set. If the network is not sufficiently accurate try initializing the network and the training again. Each time initialize a feed forward network, the network parameters are different and might produce different solutions.

The calculated error percentage between neural networks based predicted and experimental output values shown in Table.10, at each experimental condition are calculated as follows:

Error (%) = ((Experimental value- predicted value)/ Experimental value) *100 (3)

Table 10. Error analysis of neural network with experimental values.

Exp. nos.	Without carbon nano tubes Surface roughness (y) µm	Neural network without CNT Surface roughness (y) µm	% Error	With carbon nano tubes Surface roughness (y) µm	Neural network With CNT Surface roughness (y) µm	% Error
1	1.31	1.30	0.57	0.70	0.63	9.42
2	3.40	3.61	6.17	3.61	3.62	0.27
3	1.20	1.30	8.50	1.72	1.72	0.17
4	2.05	2.31	12.97	1.09	1.07	0.12
5	2.33	2.31	0.60	0.43	0.45	0.12
6	2.32	2.31	0.08	1.56	1.72	10.25
7	3.75	3.61	3.73	0.49	0.43	12.04
8	3.74	3.61	3.47	0.54	0.63	11.11
9	2.75	2.31	15.70	0.71	0.63	10.70

The range of maximum deviation in predicted error for Surface roughness for CNT based nanosteel is from 0% to 12.04% and for with CNT steel is from 0.08% to 15.7%.

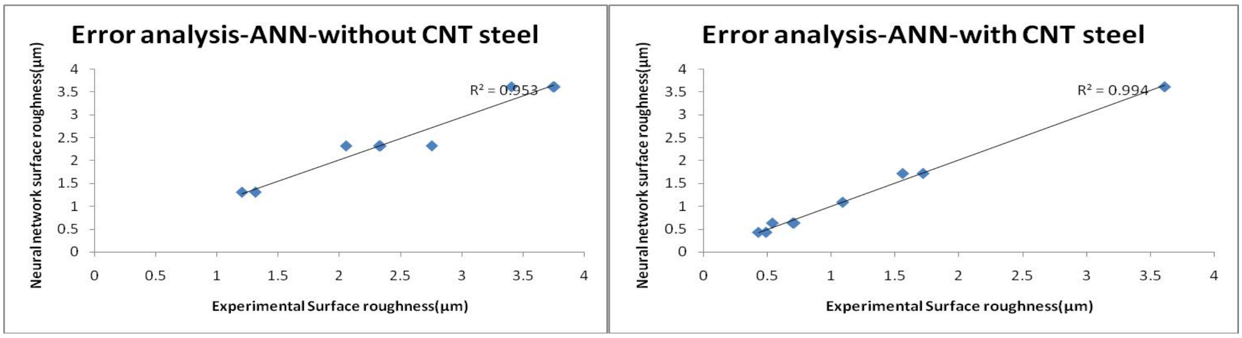

Figure 10. Error analysis of neural network with experimental values for without CNT steel (left) and with CNT steel (Right).

Figure 10 represents the error analysis of neural network surface roughness with experimental values of with CNT TMT nano steel are compared to without using CNT steel by CNC machining. The R2 value of with CNT nanosteel is 0.994 and for without CNT steel the R2 value is 0.953. The high R2 indicate that better model fit the data very well using CNT nanosteel.

CONCLUSIONS

Evaluation of surface roughness of Carbon nanotube TMT Nanosteel material using Taguchi analysis and Neural networks analysis were carried out and the following conclusion were made:

The use of Taguchi design of experiments techniques proved to be an efficient tool for the design of neural networks for surface roughness prediction in TMT nanosteel. The optimum levels of the control factors to obtain better surface roughness for with CNT were A3 (cutting speed, 1500 rpm), B1 (feed, 50 mm/ min) and C3 (depth of cut 1 mm), respectively.

Experimental results were evaluated using ANOVA and it was found that the cutting speed was the most significant factor affecting the surface roughness with a percentage contribution of 48.42% for with CNT TMT nanosteel than 38.95% for without CNT used in steel.

The powerful Levenberg–Marquardt training algorithm dramatically improved the ability to generalize and the required training time respectively. In almost 95% of the training cases early stopping would occur while not more than 6 or 7 epochs were required in the neural network training for with and without TMT nanosteel.

The predicted surface roughness from ANN model the maximum error occurs for CNT nanosteel is 12% and for without CNT steel is 15%. ANN can produce an accurate relationship between cutting parameters and surface roughness. Therefore, ANN can be used for modeling surface roughness so that it can be estimated close to real values before the machining stage.

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