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Application of Artificial Neural Network Modelling in Machining of Epoxy/TiC and Epoxy/MWCNTs Nanocomposites

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Abstract: In the present investigation, two different nanofillers were dispersed in epoxy matrix, namely, multi-wall carbon nanotubes (MWCNTs) and titanium carbide nanoparticles (TiC). Several epoxy/MWCNTs and epoxy/TiC nanocomposites containing different volume fractions of the nanofillers. The epoxy/MWCNTs and epoxy/TiC nanocomposites were machined using conventional center lathe using different cutting speeds, feed rates and depth-of-cuts to study the influence of these parameters on the surface roughness and roundness error. Based on the experimental data collected from the machining of the nanocomposites, artificial neural network (ANN) models were developed to predict the surface roughness and the roundness error as function of the volume fraction of the nanofiller, cutting speed, feed rate and depth-of-cut. The predicted results using ANN indicate good agreement between the experimental values and predicted values. For epoxy/MWCNTs nanocomposites, the developed ANN model for predicting the surface roughness and roundness error exhibited mean relative errors of 7.8% and 10.67%, respectively. While for epoxy/TiC nanocomposites, the developed ANN model exhibited mean relative errors of 6.86% and 8.39% for predicting the surface roughness and roundness error, respectively

KEYWORDS: Machining, Turning, Epoxy, Artificial Neural Networks, Nanocomposites, Surface roughness, Roundness error.

1. INTRODUCTION

Composite materials can be defined as materials consisting of two or more constituents (phases) that are combined at the macroscopic level and are not soluble in each other. One phase is called the matrix phase and the other phase is called the reinforcement. Modern synthetic composites of various types have been invented to replace metals in military, civilian, land transportation and aerospace applications [1,2].

Various types of fillers having different sizes and amounts are commonly dispersed in polymer matrices to overcome some of the limitations of the neat polymers and hence to widen the board of applications. The usage of nanoscale fillers has led to a major alternative to the conventional polymer micro-size composites [3]. Polymer nanocomposites exhibit superior physical and mechanical characteristics when compared with the micro-sized nanocomposites. This may attribute to the large interfacial area between polymers and nanofillers [4].

However, composite components are often made near-net shape, little machining is often unavoidable. In many situations, excess material is added to compensate for material conformity to complex mold shapes and also for locating and fixturing purposes. Resin flashing might also produce after molding and curing of fiber–resin preforms. This excess material must be removed by machining. Machining is also a necessary process for shaping parts from stock composite materials and for finishing tight-tolerance composite components. Some of the common used machining processes are milling, reaming, drilling, turning and grinding [5,6].

The machining process parameters are very diverse. Several process parameters such as the feed rate, cutting speed, depth-of-cut, cutting tool material and design and cooling conditions …etc. If these process parameters are not selected probably, the quality of the machined surface might deteriorate significantly. To solve this problem several optimization and predictions techniques are used such as grey relation analysis (GRA), Taguchi's analysis, response surface methodology (RSM) as well as the artificial intelligence (AI) [7,8].

The artificial neural networks (ANN) is a branch of AI that can give a precise solution for complex problems. ANNs are broadly applied to a wide range of engineering complicated problems such as machining problems of advanced materials [8-10]. The ANNs are capable to build high-level nonlinear function estimation models 3
without restrictions on the number of variables. Moreover, the ANNs are simple in use and the output results are adequately consistent and accurate for the type of application under consideration.

The objective of the current investigation is to estimate the validity of ANNs modelling technique for predicting the surface roughness and roundness error resulting from the machining by turning for epoxy/MWCNTs and epoxy/TiC nanocomposites. To accomplish this, an experimental work was conducted to prepare the epoxy-based nanocomposites and to machine them at several machining conditions of cutting speeds, feed rates and depth-of-cuts. The experiments were design using design of experiments (DoE) approach. Taguchi's approach and analysis of variance (ANOVA) were used to analyze the machining results. In ANN modelling, the independent variables are the volume fraction of the nanofiller, the cutting speed, feed rate and depth-of-cut, while the dependent variables are the surface roughness and the roundness error.

2. EXPERIMENTAL PROCEDURES

In the present investigation, the epoxy resin was used as a matrix material. The epoxy resin has a commercial name of KEMAPOXY-150. It was manufactured by Chemicals for Modern Buildings Company (CMB) - Egypt. Two types of fillers were used as reinforcements, typically, Multi-Wall Carbon Nanotubes (MWCNTs) and Titanium Carbide (TiC) nanoparticles. MWCNTs have very high tensile strength, excellent electrical conductivity, and the ability to bear high working temperatures. The TiC nanoparticles exhibit good chemical inertness and good conductivity. Figure 1 shows scanning electron microscope (SEM) micrographs of the MWCNTs and TiC nanoparticles used in the present investigation. Figure 2 shows energy dissipative x-ray (EDX) analysis of these nanofillers.

The MWCNTs have outside diameter of 30-50 nm, inside diameter of 5-10 nm, and length of 5-15 µm. The ash content in the MWCNTs is about 3.5 wt.-%. The TiC nanoparticles have diameter of 50-100 nm. The TiC nanoparticles have purity of 99%. The TiC nanoparticles appear in the form of a black powder having a spherical surface area.

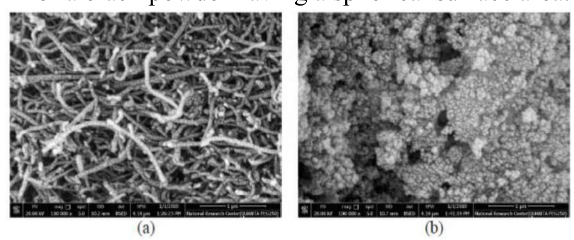

Fig 1. SEM micrographs of MWCNTs (a) and TiC nanoparticles (b) used as nanofillers

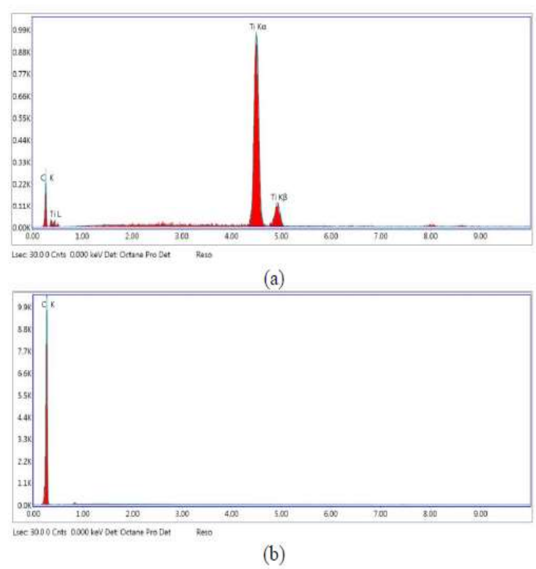

Fig 2. EDX analysis of TiC nanoparticles (a); and MWCNTs (b); nanofillers

The epoxy/MWCNTs and epoxy/TiC nanocomposites were produced by the direct mixing technique using the mechanical stirring method. The preparation steps are as follows; first, the neat epoxy resin and a certain volume fraction (0.5 or 1 vol.-%) of the nanofiller were first mixed in glass beakers, and then mechanically stirred at 300 rpm for more than 10 minutes. After that, the hardener was added to the mixture by the ratio 1:2 by vol.-% and then again stirred mechanically for 2-3 minutes. Finally, the epoxy/filler nanocomposite slurry is poured in a plastic cylindrical die, having dimensions of 50 mm diameter and 150 mm length, and allowed to fully harden at room temperature. The curing duration of the nanocomposites was about 7 days.

The cutting experiments were performed using conventional center lathe machine. The machining process was performed using uncoated carbide tip inserts having ISO designation of CNMG 120408-VM. The inserts were mounted on a tool holder of MCLNR2525M12 giving approach angle of 95o. The selection of the insert was chosen as recommended by KORLOY catalog [11]. The machining experiments of the nanocomposites were designed using Taguchi design of experiments approach based on L9 orthogonal array (OA). In a L9 OA the total number of experiments to be conducted is 9. However, each experiment was repeated three times (i.e the total number of experiments is 27). The machining variables, typically, the cutting speed (V), feed rate (F), and depth-of-cut (D) are the independent variables. The material variable (also an independent variable) was the volume fraction (Vf) of the TiC nanoparticles or MWCNTs dispersed into the epoxy matrix. The influences of these independent variables on the machining characteristics, typically, the surface roughness (Ra) and roundness error (Re) of the nanocomposites were considered. Table 1 lists the independent parameters under investigation and their levels

Table 1. The independent parameters and their levels.

Parameter	Symbol	Unit	Level 1	Level 2	Level 3
Volume fraction	Vf	Vol.-%	0	0.5	1
Cutting speed	V	rev/min	142	410	712
Feed rate	F	mm/rev	0.096	0.12	0.168
Depth-of-cut	D	mm	0.5	1	1.5

The surface roughness of the machined epoxy/MWCNTs and epoxy/TiC nanocomposites was measured using Mitutoyo Talysurf SJ-310 roughness tester. The surface roughness was determined by the arithmetic average roughness (Ra) values. The roundness error (Re), in µm, of the epoxy/MWCNTs and epoxy/TiC nanocomposites machined samples was measured using Taylor-Hobson talyrond 73 roundness tester.

ANN models were developed for prediction of the machining characteristics, typically, the surface roughness and roundness error. To achieve this, a set of multi-layer Multilayer Perceptron (MLPs) ANNs were built. Figure 3 shows the architectures of the developed MLP ANN networks. The proposed models were developed to evaluate the effect of the various cutting as well as the material parameters on the surface roughness (Ra) and roundness error (Re) of epoxy/MWCNTs and epoxy/TiC nanocomposites. The ANN calculations were performed using Statistica commercial software. To compare between predicted and the experimental values of the developed models, an error evaluation was performed using mean relative error (MRE).

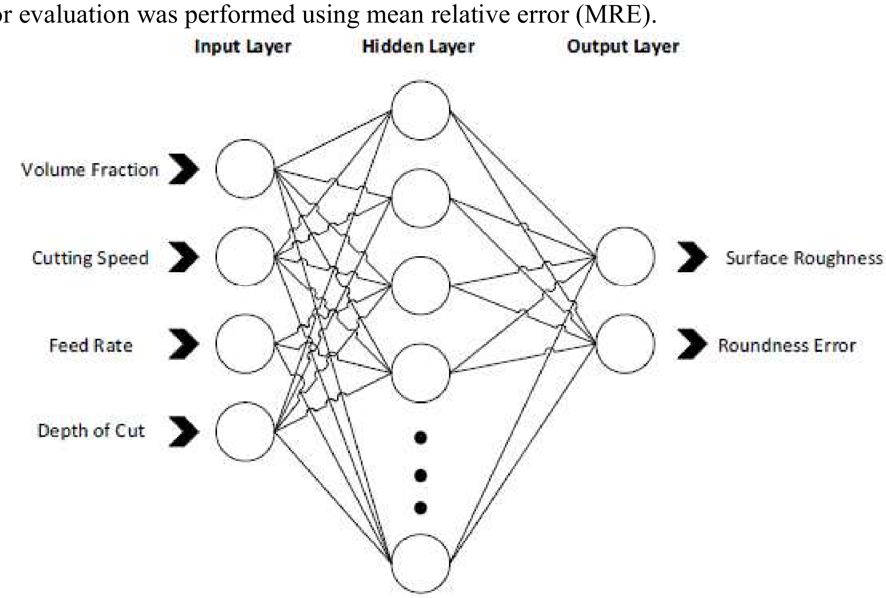

Fig 3. The architecture of MLP ANN network

3. RESULTS AND DISCUSSION

3.1. ANN modelling of the surface roughness & roundness error of the epoxy/MWCNTs nanocomposites

The ANN with MLP architecture 4-10-2 with *Exponential* transfer function exhibited the best performance among all investigated ANN networks. The ANN network shows training performance of 91.24%. Figures 4 well as the roundness error of the epoxy/TiC nanocomposites. A perfect prediction can be obtained when all the points are lied on the 45° line. The accuracy of the fitted model can be easily observed by the closeness of the data clusters to this line. It is clearly seen from the Figures that the target and predicted values are scatter around this line. The results revealed that MRE of the developed ANN model is about 7.8% and 10.67%, for the Ra and Re, respectively, which is very acceptable

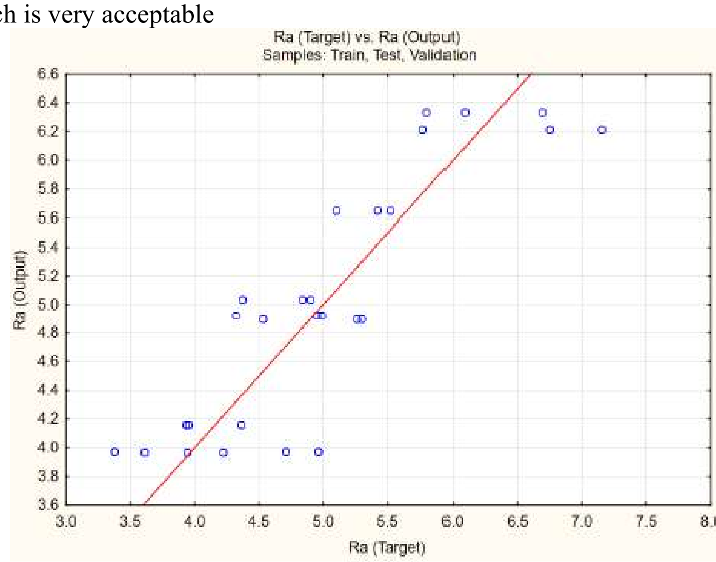

Fig 4. The target (experimental) vs. output (predicted) surface roughness (Ra) of epoxy/MWCNTs nanocomposites.

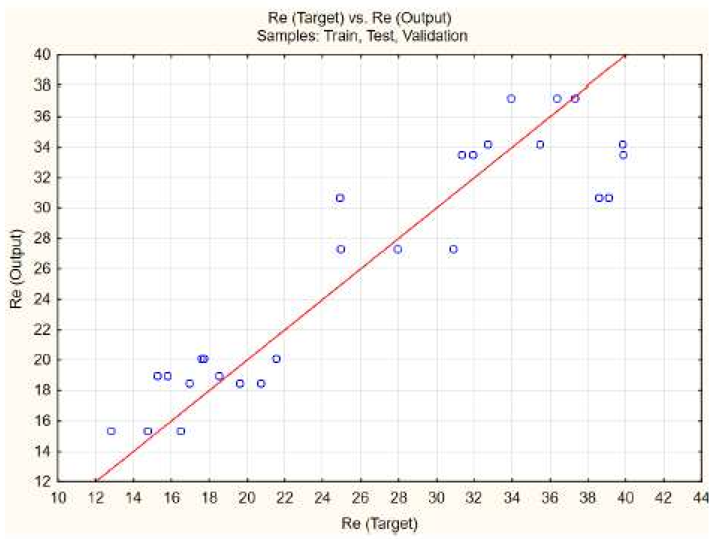

Fig 5. The target (experimental) vs. output (predicted) roundness error (Re) of epoxy/MWCNTs nanocomposites

3.2.ANN modelling of the surface roughness & roundness error of the epoxy/TiC nanocomposites

The ANN with MLP architecture 4-4-2 with *tanh* transfer function exhibited the best performance among all investigated ANN networks. The ANN network shows training performance of 90.4%. Figures 6 and 7 show comparison between the target (measured) and the predicted (output) of the surface roughness as well as the roundness error of the epoxy/TiC nanocomposites, respectively. The results revealed that MRE of the developed ANN model is about 6.86% and 8.39%, for the Ra and Re, respectively, which is very acceptable.

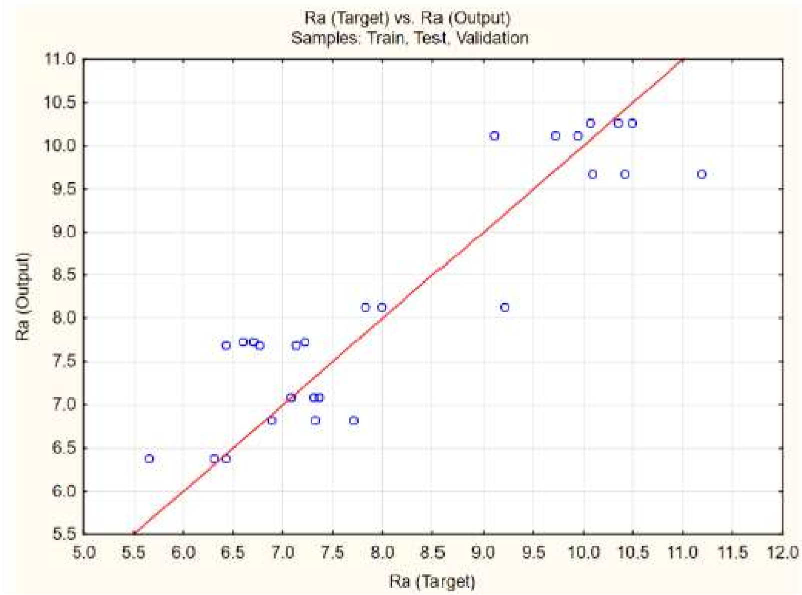

Fig 6. The target (experimental) vs. output (predicted) surface roughness (Ra) of epoxy/TiC nanocomposites

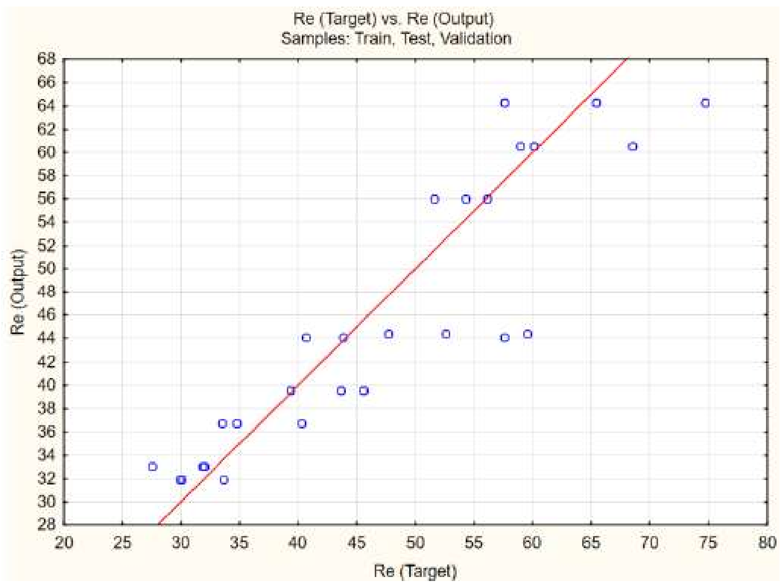

Fig 7. The target (experimental) vs. output (predicted) roundness error (Re) of epoxy/TiC nanocomposites.

4.CONCLUSIONS

1. For epoxy/MWCNTs nanocomposites, the developed neural network model for predicting the surface roughness and roundness error exhibited mean relative errors of 7.8% and 10.67%, respectively. While for epoxy/TiC nanocomposites, the developed neural network model for predicting the surface roughness and roundness error exhibited mean relative errors of 6.86% and 8.39%, respectively.

2. The neural network models developed models can be used for predicting the optimal machining parameters to obtain particular values of surface roughness and roundness error of epoxy/MWCNTs and epoxy/TiC nanocomposites. The models can be used by the machine tool manufacturers to predict the range of feed rate, cutting speed and depth-of-cut for the particular application.

REFERENCES

[1] Krishan K. Chawla, “Composite materials”, Third edition, Springer, 2012.

[2] Leonard Hollaway, “Handbook of Polymer Composites for Engineers”, Woodhead Publishing, 1994.

[3] Shaoyun Fu, Zheng Sun, Pei Huang, Yuanqing Li, Ning Hu, “Some basic aspects of polymer nanocomposites: A critical review”, Nano Materials Science, 1, 2019, pp. 2–30.

[4] A. Jumahat, C. Soutis, S. A. Abdullah, S. Kasolang, “Tensile properties of nanosilica/epoxy nanocomposites”, International Symposium on Robotics and Intelligent Sensors, Procedia Engineering, 41, 2012, pp. 1634-1640.

[5] Jamal Y. Sheikh-Ahmad, “Machining of Polymer Composites”, springer, 2009.

[6] Priyansh Patel, Vijay Chaudhary, Kundan Patel, Piyush Gohil, “Milling of Polymer Matrix Composites: A Review”, International Journal of Applied Engineering Research, 13(10), 2018, pp. 7455-7465.

[7] J. S. Pang, M.N.M. Ansari, Omar S. Zaroog, Moaz H. Ali, S.M. Sapuan, “Taguchi design optimization of machining parameters on the CNC end milling process of halloysite nanotube with aluminium reinforced epoxy matrix (HNT/Al/Ep) hybrid composite”, HBRC Journal, 10, 2014 pp. 138–144.

[8] N. Venkateshwaran, A. Elayaperumal, A. Alavudeen and M. Thiruchitrambalam, “Review of Artificial Neural Network and Taguchi Application in Polymer Matrix Composites”, Rev. Adv. Mater. Sci., 29, 2011, pp. 100-103.

[9] S. Manoj, V.C. Sathish Gandhi, K. Vigneshwaran, M. Rajkumar, S. Niranjan, “Review on Optimization of Process Parameters using Artificial Neural Network”, International Journal of Engineering, Science and Mathematics, 7(4), 2018, pp. 345-361.

[10] M. R. Dashtbayazi, M. Ghanbarian, “Comparison of Artificial Neural Network Methods in Modeling of Polymer Matrix Composite Turning”, Amir Kabir Journal of Science & Research (Mechanical Engineering) (ASJR-ME), 47(2), 2015, pp. 33-36.

[11] Korloy, Cutting Tools Catalog, 2018.