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Modeling and Simulation of Cutting Tool Temperature in Turning Process of C45 Alloy Steel Using Artificial Neural Network (ANN)

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Abstract – *Cutting tool temperature is generally classified as the most important technological parameters in machining processes due to their significant impacts on the product quality. A large number of interrelated machining parameters have a great influence on the cutting tool temperature so it is quite difficult to develop a proper theoretical model to describe efficiently and accurately a machining process. In this paper, an artificial neural network (ANN) model using MATLAB program for predicting cutting tool temperature and surface roughness during hard turning of alloy steel C45 is proposed. This paper is based on an experimental dataset of cutting tool temperature and surface roughness measured during hard turning process. Rotational speed (rpm), depth of cut (mm) and feed rate (mm/rev) are taken as input parameters of the ANN model. However, the surface roughness and the cutting tool temperature are the outputs. The ANN model consists of a multi-layer feed-forward which is trained by a back-propagation (BP) algorithm. The influence of double hidden layer (instead of a single hidden layer) is taken into account. However; a various number of neurons in the hidden layer are also tested. It was found that, the ANN model showed a reasonable agreement with the experimental results, therefore it is considered to be a trusted means of modeling and simulating the turning process. It is found also that increasing the speed of rotation of the turning process increased the cutting tool temperature. The maximum temperature recorded during the process was 110°C at a=2 mm, S=0.2 mm/rev and N=1500 rpm. In addition to that, increasing the feed rate and rotational speed gave a low level of surface roughness. Finally, it showed that both of the rotational speed and feeding rate have a significant impact on the surface roughness, however, the cutting depth has not a sufficient effect on the average surface roughness.*

Key Words: turning process, cutting tool temperature, C45, ANN, feed rate, depth of cut, surface roughness.

1.INTRODUCTION

Generally, machining is the major process used in manufacturing particularly to surface finish the mechanical parts. The costs of these operations and final product quality are highly constrained to competitive environment, where investors looking for higher return on their investments. Cutting tool temperatures during the machining process affect some process parameters, such as dynamic stability, tool wear, work piece surface integrity and geometrical dimensions. Cutting tool temperature modeling is so necessary, as it permits to characterize material machinability to get some knowledge on the power required during machining, to monitor tool wear and to predict surface roughness [1-3]. Cutting tool temperature is related to various process parameters such as tool material, workpiece properties and cutting conditions such as feed rate, cutting speed and depth of cut [4-5]. It is then difficult to provide an accurate theoretical model to describe complex machining processes such as milling and turning.

Many investigators have employed the heuristic optimization techniques to identify the optimal cutting parameters. D'Addona et al. [6] used the genetic algorithm to identify the optimized turning parameters and investigated the tool wear and its pattern by applying the DNA-based computing. However; Marko et al. [7] applied the particle swarm optimization to identify the optimized turning parameters. Prasanth and Raj [8] estimated the optimal cutting parameters of a cylindrical turning process by using the artificial bee colony algorithm. On the other hand, Amer et al [9] studied the optimized turning parameters by integrating the genetic algorithm with support vector regression and the artificial neural networks. Bruni et al. [10] modeled the surface finish milling under dry cutting conditions by applying the artificial neural networks (ANN).

Investigators have also identified the efficient use of ANN models on other metal machining processes such as, the prediction of cutting forces, machining vibrations, tool wear rate, milling and drilling and the skin pass rolling [14], etc. Similarly, ANNs have been applied effectively to determine the machining, surface roughness and the optimal cutting conditions [11-17]. In this study, the ANN is considered because of the complex nonlinear optimization problem of the case under consideration. As compared to the traditional approaches, the ANN can learn the solutions and predict the complex interactions of the input and output data with significant accuracy [18]. The ANN function was inspired by the natural biological neurons, which act as parallel distributed processors [19]. Neurons have the capability for sorting and storing the empirical knowledge, and to generate the output from a series of the inputs. The basic components of a neural network comprise neutrons (nodes or processing element) and the synaptic weights (connections). The synaptic weights with a positive and negative value represent the excitatory and inhibitory connection. Inputs weighted by the respective synaptic weights are accumulated together, which represent the accumulating function. The summation result is passed on to an activation function (non-linear) which determines the neuron response. Artificial neural network (ANN) approach is routinely considered as an accurate and powerful tool for machining process modelling, as it permits to save much time and money generally spent in experimental procedures. A large amount of works has been carried out on forces modelling, which have shown that ANN approach is more accurate and faster than many other analytical and numerical cutting force modelling methods. In the work conducted in [20], an approach for cutting forces modelling has been developed based on feed-forward multi-layer neural networks trained by BP algorithm, and applied to experimental machining data. Specs have investigated the effect of two of the main parameters which influence error convergence: learning rate η and momentum term α. While the used analytical model gives an average prediction error of 9.5% on cutting forces, his neural network provides predictions in training with an average error of 3.5%. In [21-22] have investigated supervised ANN approach to estimate forces generated during end milling process. They have found that the radial basis network requires more neurons than the standard feed forward neural network with BP learning rule and that feed forward neural network gives more accurate results, but takes 70% much time.

In this study, an ANN model will be proposed to predict the cutting tool temperature and average surface roughness in the dry turning process of steel C45 under the effect of the three cutting parameters (Rotational speed, feed rate and depth of cut) and the ANN model results will be compared with the experimental results.

2. EXPERIMENTAL TESTS

The steel C45 material with a maximum carbon steel solubility of 0.45 and chemical composition as shown in Table 1 is used in this experimental work. It has been chosen for this experiment due to its importance in mechanical industries and also for their mechanical properties. So, a cylindrical specimen of C45 alloy steel of 250 mm long and 30 mm diameter is installed on the CNC lathe machine of Spinner TC42 Type as shown in Figure 1. A thermocouple of K-Type is used in this experiment by inserting it in a prepared slot in the cutting tool and connected directly to a MATLAB program to record the data directly for further analysis.

Table -1: C45 Physical and Mechanical Properties, Prasanth [8].

quantity	Value	Unit
Thermal Conductivity	25	w/m.K
Specific Heat	460	J/kg.K
Melting Temperature	1450-1510	°C
Density	7700	Kg/m³
Young's Modulus	2000	MPa
Tensile Strength	650-880	MPa
Elongation	8-25	%
Fatigue Strength	275	MPa
Yield Strength	350-550	MPa

Fig – 1: CNC Lathe machine (Spinner TC42)

These experiments have been performed at 3 rotational speeds of 900, 1200 and 1500 rpm. And three feed rate of 0.1, 0.15 and 0.2 mm/rev have been also performed during the experiment and at depths of cut of 1, 1.5 and 2 mm respectively.

A total of 150 readings per sample were taken, one reading every five seconds. This was performed for all samples in dry operation, and then was recorded using the MATLAB program. The roughness of each tested sample was also measured through a mobile roughness measurement device as shown in Figure 2, where five roughness values were taken on the surface of each sample. This numerical technique is based mainly on a dataset provided by experimental hard turning process of C45 alloy steel using conventional cutting tools as mentioned previously. Three components have been experimentally determined for 27 different and cutting condition combinations (Rotational speed n, feed rate f and depth of cut a) as shown on Table 2. The first 19 cases mentioned in Table 2 are used to train the network. However; the left 8 are testing conditions. The main objective is then to develop an ANN model to properly predict cutting parameters conditions that influence on cutting tool temperature and surface roughness during this hard turning. This model will be valuable in the same ranges as training cutting conditions.

Table-2: Experimental training dataset, [23].

NO	Cutting parameters			Measured temperature and surface roughness	
	N (rpm)	S (mm/rev)	a (mm)	T (°C)	Ra (μm)
1	900	0.1	1	59	1.2400
2	1200	0.1	1	82	1.1090
3	1500	0.1	1	88	1.0210
4	900	0.15	1	76	1.5400
5	1200	0.15	1	80	1.3406
6	1500	0.15	1	88	1.2670
7	900	0.2	1	89	2.2900
8	1200	0.2	1	91	2.1820
9	1500	0.2	1	96	1.8833
10	900	0.1	1.5	93	2.7870
11	1200	0.1	1.5	86	1.5200
12	1500	0.1	1.5	94	1.0163
13	900	0.15	1.5	70	1.9843
14	1200	0.15	1.5	90	1.4400
15	1500	0.15	1.5	100	1.3033
16	900	0.2	1.5	91	2.1036
17	1200	0.2	1.5	93	2.7300
18	1500	0.2	1.5	101	1.8086
19	900	0.1	2	104	1.4400
20	1200	0.1	2	107	1.0873
21	1500	0.1	2	100	0.8433
22	900	0.15	2	102	1.9953
23	1200	0.15	2	109	1.4266
24	1500	0.15	2	103	0.7223
25	900	0.2	2	97	2.2323
26	1200	0.2	2	103	2.2686
27	1500	0.2	2	110	1.3293

Fig – 2: Surface roughness measurement device.

3. NEURAL NETWORK MODEL DEVELOPMENT AND OPTIMIZATION

An Artificial Neural Networks is considered as an artificial intelligence modeling technique which has a highly interconnected structure similar to brain cells of human neural networks. It consists of a large number of simple processing elements called neurons, which are arranged in different layers in the network and can be classified as the input layer, output layer and one or more hidden layers [24]. In this work, an artificial neural network model is developed to predict the surface roughness and cutting tool temperature by knowing the affecting parameters such as speed of rotation, depth of cut and feed rate. Generally there are no equations which connect these different factors to calculate the surface roughness and cutting tool temperature, so, it becomes so important to develop such a model. In the experiments; 27 datasets that shown in Table 2, were for developing a neural network model, 19 of them were used as training the program and the left 8 have been used for testing the program as mentioned previously. The number of training data is taken to be approximately equal to 70% of the total data, while the numbers of testing data are taken randomly to be approximately equal to 30% of the total data. The development of ANN requires the selection of number of hidden layers and the neurons in each of hidden layer from the best activation function. The trials and errors have been carried out to choose the best number of hidden layers and the number of neurons in each hidden layer.

The number of neurons in the first hidden layer was selected by trial and error. It started with a relatively small number of neurons (20 neurons) and increased until the approximation is satisfied for the network as shown in Figure 3. It is observed that the best performance and correlation coefficient for both training and testing were achieved with nodes in the hidden layer with activation function as hyperbolic tangent (tansig) and (purelin) function, and (trainrp) as training function.

The numbers of neurons in the second hidden layers were also selected by using trial and error with different neurons in each hidden layer starting from 5 to 8 in each hidden layer. The performance and the regression of these networks for both training and testing data are considered. It is found that the network with (11-9) nodes (11 nodes in the first hidden layer and 9 in the second hidden layer) with training function as Conjugate Gradient type (trainscg) as clear in Figure 3 gives better performance and correlation coefficient for both training and testing than the other trials.

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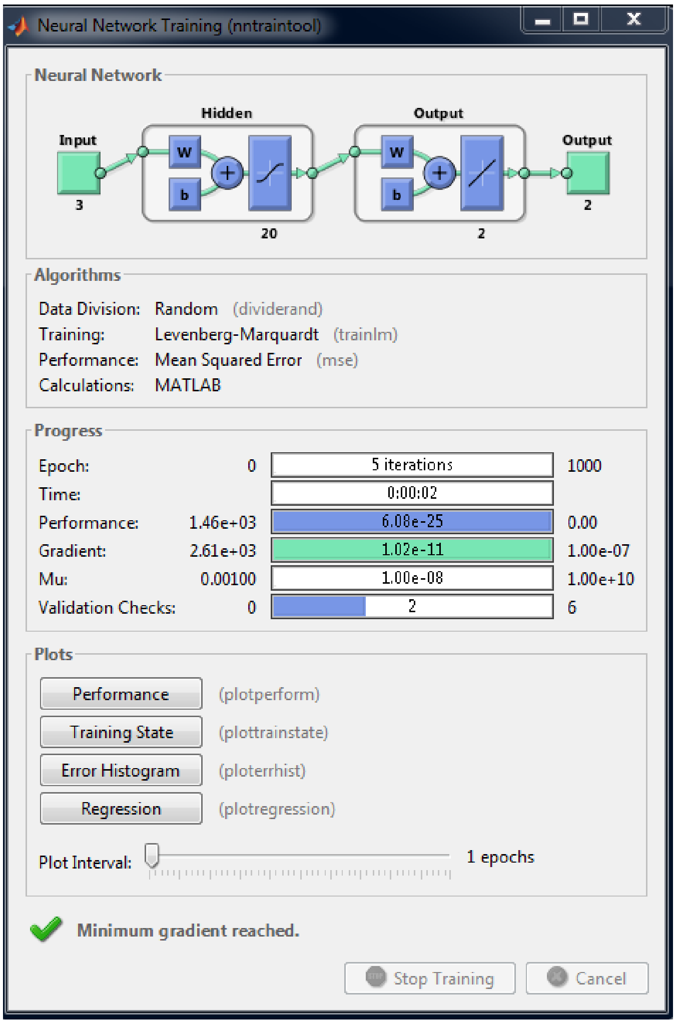

Fig – 3: Neural Network Training (nntraintool)

After finding out the best function with the number of neurons in the first and second hidden layers, the performance of these networks was compared with each other to find the best one. It is found that the second hidden layers with training function (trainscg) and 11-9 nodes gives the best performance and a correlation coefficient, therefore it is selected as the best network in the present work.

Figure 4, shows the configuration of the suggested artificial neural network (3-11-9-2) neurons (11 neurons in the first hidden layer and 9 in the second). However, 3 refers to number of inputs, and 2 refers to the number of outputs.

The regression analysis between the output of neural network and the corresponding target for training and testing data are shown in figure 5 for cutting tool temperature and surface roughness, respectively. The predicted values compared with the target values showed an excellent agreement. The correlation coefficient (R-value) between the outputs and targets can be defined as a measure of how well the variation in the output is explained by the targets. If this number is equal to 1, then there is a perfect correlation between targets and outputs. The dotted line in Figure 5 indicates the best line fit and the solid line indicates the perfect fit (output equals targets). The experimental and predicted values are very close to each other, which mean that the proposed ANN model has a high correlation factor for cutting tool temperature and surface roughness training and testing R=0.99832 and R=0.98402, respectively as shown in Figure 5. It shows also the cutting tool temperature factor of R=0.99213 and R=0.99450 for training and testing of temperature respectively.

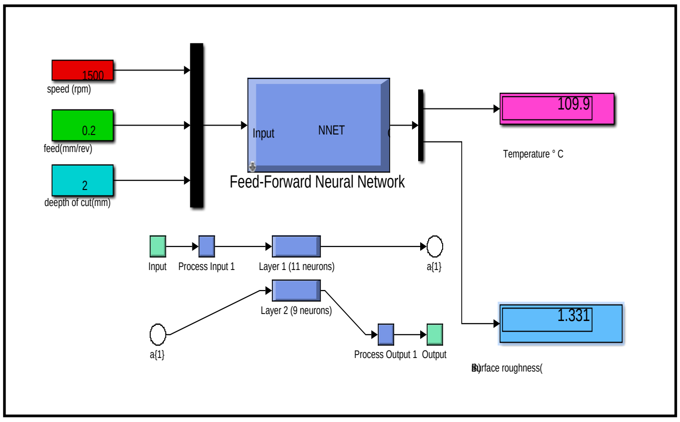

Fig -4: Configuration of the Neural Network (3-11-9-2)

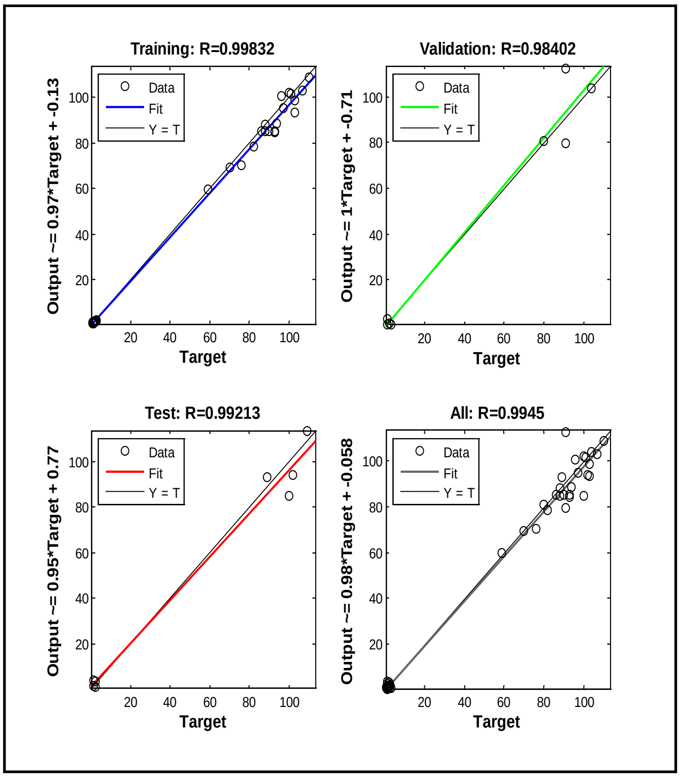

Fig -5: Correlation factor of cutting tool temperature ANN.

4. RESULTS AND DISCUSSIONS

The measurement of the cutting tool temperature for metal turning process was performed to determine the change of it at changing one of the active factors such as rotational speed, feed rate and depth of cut. The experimental results of the measurement of the cutting tool temperature against time are shown clearly in Figures from 6 to 14. These figures show the change of temperature of a sample over a sample of time which indicate that the temperature increase generally to a certain value and after it will be stable as shown in all figures. For example, Figure (6) shows the highest temperature of 88°C that is recorded at a=1mm, s=0.1 mm/rev and N=1500 rpm compared to the other two samples as shown in the same figure. However; a highest temperature of also 88°C is recorded at a=1 mm, S=0.15 mm/rev and N=1500 rpm as shown clearly in figure (7) and 96°C at a=1 mm, S=0.2 mm/rev and N=1500 rpm as clear in figure (8).

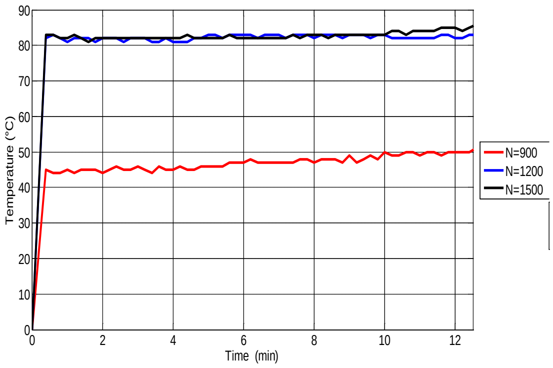

Fig -6: Temperature against Time for different speeds at S=0.1 mm/rev and a=1 mm.

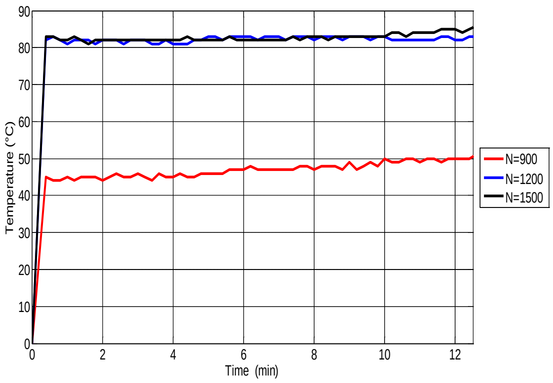

Fig -7: Temperature against Time for different speeds at S=0.15 mm/rev and a=1 mm.

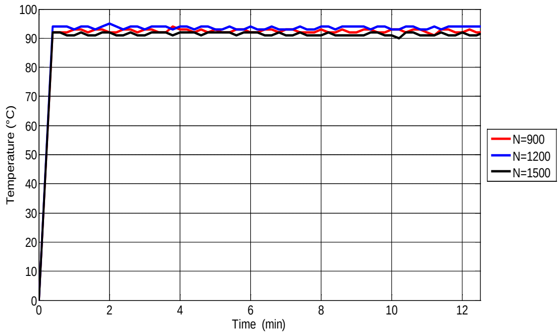

Fig -8: Temperature against Time for different speeds at S=0.2 mm/rev and a=1 mm.

Figure (9) and Figure (10) show the highest temperature of 94 and 100°C at a=1.5 mm, S=0.1 mm/rev, N=1500 rpm and a=1.5 mm, S=0.15 mm/rev and N=1500 rpm respectively. The highest temperature of 104°C recorded at a=1.5 mm, S=0.2 mm/rev and N=1500 rpm is shown in figure (11).

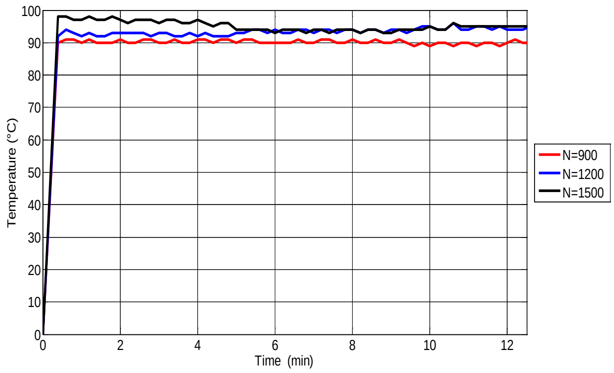

Fig -9: Temperature against Time for different speeds at S=0.1 mm/rev and a=1.5 mm.

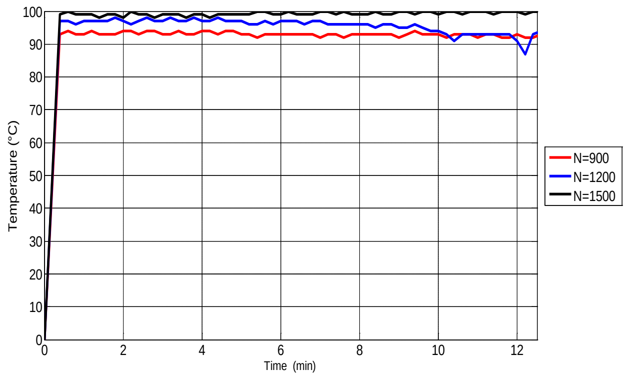

Fig -10: Temperature against Time for different speeds at S=0.15 mm/rev and a=1.5 mm.

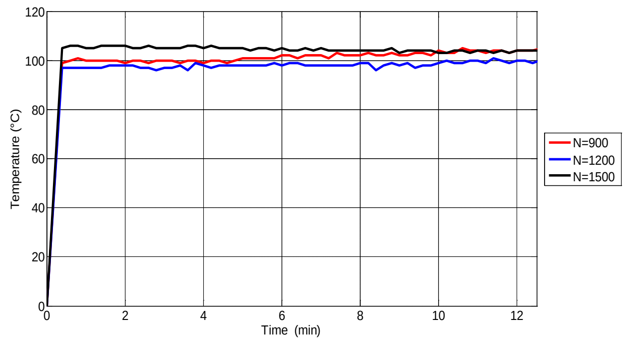

Fig -11: Temperature against Time for different speeds at S=0.2 mm/rev and a=1.5 mm.

Figure (12) and Figure (13) show the highest temperature of 102 and 103°C at a=2 mm, S=0.1 mm/rev, N=1500 rpm and a=2 mm, S=0.15 mm/rev and N=1500 rpm respectively. The highest temperature of 110°C recorded at a=2 mm, S=0.2 mm/rev and N=1500 rpm is shown in figure (14).

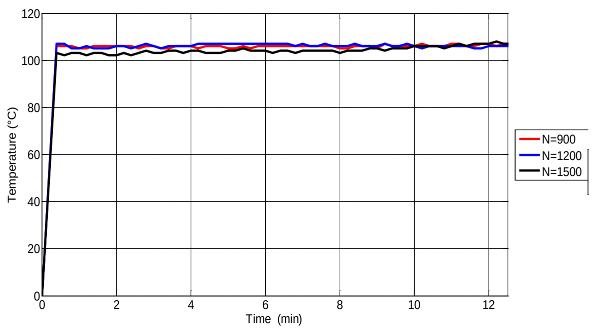

Fig -12: Temperature against Time for different speeds at S=0.1 mm/rev and a=2 mm.

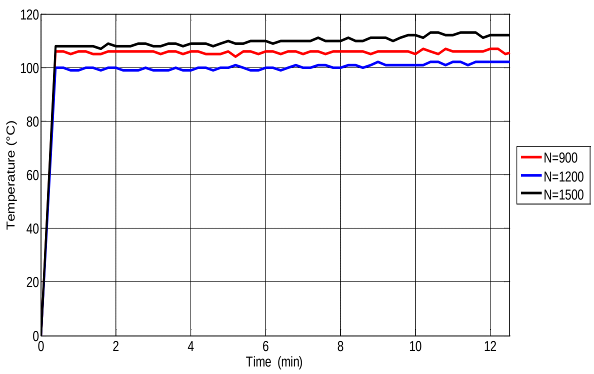

Fig -13: Temperature against Time for different speeds at S=0.15 mm/rev and a=2 mm.

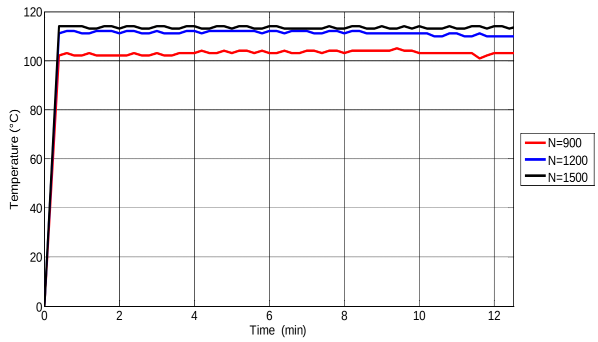

Fig -14: Temperature against Time for different speeds at S=0.2 mm/rev and a=2 mm.

5. ARTIFICIAL NEURAL NETWORK

The final optimal structure of neural network model that used in cutting temperature and surface roughness (3-11-9-2) which is previously shown in Figure 4 is ready for collecting the data. The cutting tool temperature coefficient in this model is 0.99832and 0.98402 for training respectively, with mean square error 0.000034, while 0.99213 and 0.99450 for testing, respectively with mean square error 0.042 and training function (trainscg). Figures 15 and 16 show the comparison between the ANN model results and the experimental results of both cutting tool temperature and surface roughness. It shows a satisfactory agreement between the experimental results and the ANN model results.

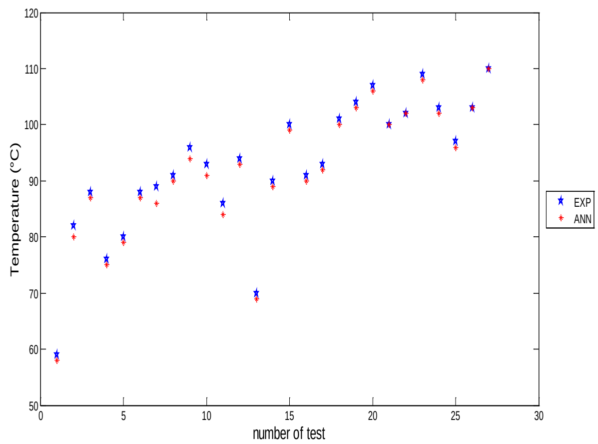

Fig -15: The experimental and predicted ANN model results of cutting tool temperature.

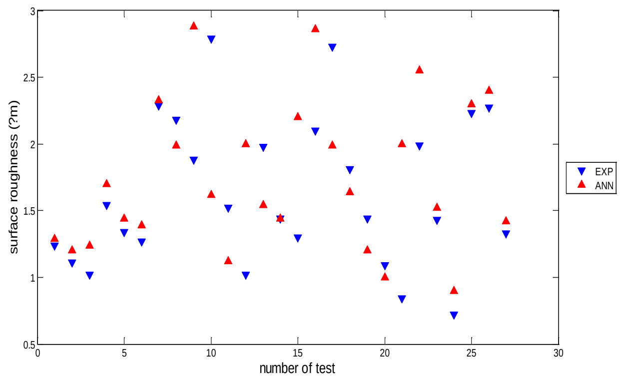

Fig -16: The experimental and predicted ANN model results of surface roughness

6. CONCLUSIONS

From the results of the present study, the important conclusions are as follows:

1- The ANN with two hidden layers consist from 11 nodes in the first hidden layer and 9 nodes in the second with training function as conjugate gradient (trainscg) has been successfully used to predict the cutting temperature and surface roughness. The ANN model showed a reasonable agreement with the experimental results.
2- There is a significant relationship between the cutting parameters (speed of the rotation, depth of cut and feed rate) and the average cutting tool temperature in the dry operation of turning process.
3- Increasing the speed of rotation in the operation of turning process increase the cutting tool temperature.
4- Increasing the depth of cut and the speed of rotation together has a higher effect on the cutting tool temperature.
5- Feed rate value affected slightly the temperature compared to speed of rotation and depth of cut.
6- Increased feed rate and speed of rotation give a low level of surface roughness.
7- Increasing the speed of rotation and reducing the depth of cut leads to a decrease in surface roughness.
8- Finally, the speed of and feeding have a significant impact on the low average roughness and the depth of cutting has not a sufficient effect on the average roughness.

REFERENCES

1- Dimla, D. E., "Application of perception neural networks to tool state classification in metal-turning operation. Elsevier", Engineering Applications of Artificial Intelligence, 12, 471–477, 1999.
2- Liu, T. L., Chen, W. Y., Anantharaman, K. S., "Intelligent detection of drill wear" Elsevier, Mechanical Systems and Signal Processing, 12, 863–873, 1998.
3- Ezugwua, E. O., Fadarea, D. A., Bonneya, J., Da Silvaa, R. B., Salesa, W. F., "Modelling the correlation between cutting and process parameters in high speed machining of Inconel 718 alloy using an artificial neural network" Elsevier, International", Journal of Machine Tools and Manufacture, 45, 1375–1385, 2005.
4- Oxley, P. L. B., "Modeling machining processes with a view to their optimization and to the adaptive control of metal cutting machine tools, Elsevier" Robotics and Computer - Integrated Manufacturing, 4, 103-119, 1988.
5- Budak, E, Ozlu, E., "Development of a thermo mechanical cutting process model for machining process simulations", CIRP Annals-Manufacturing Technology, 57, 97-100, 2008.
6- D' Addona, D.M.; Teti, R., "Genetic algorithm-based optimization of cutting parameters in turning processes" Procedia CIRP 2013, 7, 323–328.
7- Marko, H.; Simon, K.; Tomaz, I.; Matej, P.; Joze, B.; Miran, B. "Turning parameters optimization using particle swarm optimization" Procedia Eng. 2014, 69, 670–677.
8- Prasanth, R.S.S.; Raj, K.H. "Optimization of straight cylindrical turning using Artificial Bee Colony (ABC) algorithm" J. Inst. Eng. Ser. C 2012, 98, 171–177.
9- Amer, F.Z.; El-Garhy, A.M.; Awadalla, M.H.; Rashad, S.M.; Abdien, A.K. "A real-valued genetic algorithm to optimize the parameters of support vector machine for classification of multiple faults in NPP" Nukleonika 2011, 56, 323–332.
10- Bruni, C.; D'Apolito, L.; Forcellese, A.; Gabrielli, F.; Simoncini, M. "Surface roughness modeling in finish face milling under MQL and dry cutting conditions" Int. J. Mater. Form. 2008, 1, 503–506.
11- Sick, B. "On-line and indirect tool wear monitoring in turning with artificial neural networks: A review of more than a decade of research" Mech. Syst. Signal 2002, 16, 487–546.
12- Ezugwu, E.O.; Fadare, D.A.; Bonney, J.; Da Silva, R.B.; Sales, W.F. "Modeling the correlation between cutting and process parameters in high-speed machining of Inconel 718 alloy using an artificial neural network" Int. J. Mach. Tools Manuf. 2005, 45, 1375–1385.
13- Çaydas, U.; Hasçalik, A. "A study on surface roughness in abrasive waterjet machining process using artificial neural networks and regression analysis

method" J. Mater. Process. Technol. 2008, 202, 574–582.

14- Mahmood khani, Y.;Wells, M.A.; Song, G. "Prediction of roll force in skin pass rolling using numerical and artificial neural network methods" Ironmak. Steelmak. 2017, 44, 281–286.

15- Ranganathan, S.; Senthilvelan, T.; Sriram, G. "Evaluation of machining parameters of hot turning of stainless steel (type 316) by applying ANN and RSM. Mater" Manuf. Processes 2010, 25, 1131–1141.

16- Chang, C.K.; Lu, H.S. "Study on the prediction model of surface roughness for side milling operations" Int. J.Adv. Manuf. Technol. 2006, 29, 867–878.

17- Pal, S.K.; Chakraborty, D. "Surface roughness prediction in turning using artificial neural network" Neural Comput. Appl. 2005, 14, 319–324.

18- Cus, F.; Zuperl, U. "Approach to optimization of cutting conditions by using artificial neural networks" J. Mater. Process. Technol. 2007, 173, 281–290. 29.

19- Reddy, N.S.K.; Rao, P.V. "Selection of optimum tool geometry and cutting conditions using a surface roughness prediction model for end milling" Int. J. Adv. Manuf. Technol. 2005, 26, 1202–1210.

20- Umbrello, D.; Ambrogio, G.; Filice, L.; Shivpuri, R.A. "Hybrid finite element method-artificial neural network approach for predicting residual stresses and the optimal cutting conditions during hard turning of AISI52100 bearing steel" Mater. Des. 2008, 29, 873–883.

21- Haykin, S. "Neural Networks A Comprehensive Foundation" 2nd ed.; Pearson: McMaster University, Hamilton,ON, Canada, 1999.

22- Szecsi, T., "Cutting force modeling using artificial neural networks, Elsevier", Journal of Materials Processing Technology, 92-93, 344- 349, 1999.

23- F. Abdullah, Sabreen A. Abelwahab, Yasser Fatouh, Ibrahim Ahmed "Operation zone temperature control in CNC machines and their educational applications" PhD under progress, Faculty of Industrial Education , Helwan University, Cairo, Egypt, 2019.

24- Zuperl, U., Cus, F., "Tool cutting force modeling in ball-end milling using multilevel perceptron, Elsevier", Journal of Materials Processing Technology, 153–154, 268–275,2004.

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