EXPERIMENTAL STUDY ON STAINLESS STEEL FOR OPTIMAL SETTING OF MACHINING PARAMETERS USING TAGUCHI AND NEURAL NETWORK

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ABSTRACT

Stainless steels (SS) are used for many commercial and industrial applications for their excellent corrosive resistance. SS are generally difficult to machine material due to their high strength and high work hardening tendency. Tool wear (TW) and surface roughness (SR) are widely considered most challenging aspect causing poor quality in machining of SS products. Optimization of cutting parameter is essential for the achievement of high quality and high rate of mass production. In this work, optimum cutting parameters for each performance measure is obtained by employing Taguchi techniques. The orthogonal array, signal to noise ratio and analysis of variance (ANOVA) are employed to study the performance characteristics in turning operation and SR and TW of the multilayer coated cutting tool for CNC turning of austenitic stainless steel (AISI 316) under are taken as responses for analysis. Further the multi layered feed forward artificial neural network (ANN) is developed to predict the SR and TW during turning process. Finally predicted responses were compared with the respective measured values and absolute percentage error was computed.

Keywords: CNC turning, surface roughness, tool wear, Taguchi's techniques, ANOVA, artificial neural network.

1. INTRODUCTION

The challenges which are made by the modern machining industries is mainly focused on the achievement of high quality, in terms of work piece dimensional accuracy, SR, high production rate, less TW on the cutting tools, economy of machining in terms of cost saving and increase the performance of the product with reduced environmental impact [1]. A surface property such as roughness is critical and increasing component to the function ability of machined components [2, 3]. TW which results in tool substitution is one of the most important economical penalties, so that it is very important to minimize TW, and optimize all the cutting parameters [4]. Normally, AISI 316 are generally regarded as more difficult to machine materials than carbon and low alloy steels due to their high strength, ductility and high work hardening tendency [5, 6]. Coated carbides are basically a cemented carbide insert coated with one or more thinly layers of wear resistant materials, such as titanium nitride, titanium carbide and aluminum oxide. It is well known that coating can reduce tool wear and improve the SR [7]. Therefore, most of the carbide tools used in the metal cutting industries is coated while coating brings about an extra cost [8]. Effect of cutting parameters on AISI 316 was investigated with multilayer coated by TiC/TiCN/TiN and TiC/TiCN/Al_2O_3 under dry conditions [9]. Surface roughness model was developed for turning of AISI 316 with TiN/Al_2O_3/TiC coated carbide tool [10]. Friction coefficient model was developed between tool and work during the turning of AISI 316 with TiN coated carbide tool [11]. Limited research papers only available turning of AISI 316. More Research is needed to determine how cutting parameters affect TW and SR. various coating materials are provided different properties. So, in this work multilayered with TiCN-Al_2O_3 tool is used for turning process.

Optimization of cutting parameter is necessary for the achievement of minimal TW and SR. The Taguchi method of experimental design is one of the widely accepted techniques for off line quality assurance of products and processes. This method is a traditional approach for robust experimental design that seeks to obtain a best combination set of factors and levels with the lowest social status of cost solution to achieve customer requirements [12]. The main concept of the this technique is the use of parameter design, which is an engineering method for product or process design that focuses on determining the parameter settings which can be produced at the best levels of quality characteristic with minimum variation. Taguchi design provides a powerful and efficient method for designing processes that operate continuously and optimally over a variety of conditions [13]. Experimental design methods were developed in the early of 20th century and have been extensively studied by some of the statistical ideas, but they were not easy to use by practitioners [14]. So Taguchi method is recommended for solutions in metal cutting problems to optimize the cutting parameters [15].

The predictions of SR and TW in machining are a major demanding task, but due to this complexity and uncertainty of the machining process in modeling and optimization of CNC turning, it is very difficult to provide an accurate model with traditional identification of methods. Instead of them, artificial intelligence (AI), process models such as ANN, fuzzy sets, genetic algorithms etc. are used for optimizing, predicting or controlling machining processes [16, 17]. Mostly ANN, fuzzy logic and genetic algorithm are used to estimate responses and monitoring online machining processes. The

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researchers have made an effort to the solution of non linear problems. The ANN has the ability to approximate any complex relationships between process performance variables and process variables in machining accurately, hence is well suited for the prediction of SR, TW and for use in reliable model of highly non linear process [18, 19].

When the experimentation is costly and time-consuming, is very important that an effective proper planning of experimentation is essential to be reduced. Researcher have used many methods to predict responses, but combination of these methods not been done for CNC turning on AISI 316 by multilayered tool. In this paper Taguchi method is used to optimize the performance characteristics of process parameters and tool condition monitoring system that predicts the SR and TW using a multi-layer feed forward ANN trained with error back propagation (BB) training algorithm is employed for turning operation.

2. MATERIALS AND METHODS

The work material used for the present investigation is AISI 316. The diameter of the material is 32mm and machined length is 60mm for all trials. The chemical composition of the work material is given in Table-1.

Table-1. Chemical composition of AISI 316.

	Si	Mg	P	S	Ni	Cr	Mo
0.040	0.498	1.560	0.036	0.017	10.45	16.71	2.112

2.1 Taguchi method

This paper uses Taguchi method for optimization of cutting parameters in machining of AISI 316, which is very attractive and effective method to deal with responses influenced by number of variables. In this method, main parameters are assumed to have influence on process results, which are located at different rows in a designed orthogonal array. With such an arrangement completely randomized experiments can be conducted. This method is useful for studying the interactions between the parameters, and also it is a powerful design of experiments tool, which provides a simple, efficient and systematic approach to determine optimal cutting parameters. Compared to the conventional approach of experimentation, this method reduces significantly the number of experiments that are required to model the response functions. There are three categories of quality characteristic in the analysis of the S/N ratio, (1) the-lower-the-better, (2) the-higher-the-better and (3) the-nominal-the-better. Since the quality characteristic is to be minimized, the-lower-the-better category is used to calculate the S/N ratio for SR and TW. Equation (1) shows the lower the better characteristic.

$$\eta = -10\log_{10}\ 1/n\Sigma_i^n y^2 \quad \ldots\ldots(1)$$

Where

η = Signal to noise ratio
n = Number of repetitions of experiment
y = Measured value of quality characteristic.

2.2 Artificial neural networks

The experimental data setup is composed mainly of a medium and high number of samples, since the data set is usually divided for training, testing and validating. The multi-layer feed forward ANN employed in current study consists of simple processing elements called neurons divided into input layer, output layer and hidden layers. The neurons between the layers are connected by the weight of links. Each neuron has inputs and generates an output as the reflection of local information stored in connections. The output of each neuron is determined by the level of the input signals in relation to the threshold value. These signals are modified by the connection weights between the neurons. The output of a neuron is intake and supplied to other neurons of adjacent layers as input signals via interconnections. The BB algorithm proceeds as follows: Firstly, inputs are presented to the network and errors are computed; secondly, sensitivities are propagated from the output layer to the input layer; then, weights and biases are updated. The error BB training algorithm is based on weight updates so as to minimize the sum of squared error for outputs neurons. The training process is started by assigning a small random weight and threshold values to all the links. For training the normalized input patterns and corresponding output data was used. The input - output patterns are presented one by one and updating the synaptic weights each time. The sum of the mean squared error between the estimated network output and the target output of all patterns at the end of the each iteration is computed. The training process is stopped when the determined target number of iteration obtained, and the last updated weight values are stored about to use in the test phase. The architecture and feature of the three layers NN developed are shown in Figure-1.

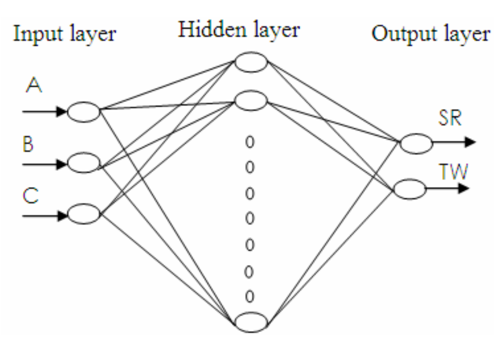

Figure-1. Multi-layered feed forward ANN architecture.

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3 Experimental details

The experiments were conducted on Fanuc CNC lathe. Multilayered CNMG 120408 coated with TicN+Al_2O_3 of 14 μm is used as the insert for all machining operation. The range of cutting parameters were selected based on past experience, data book and available resources. SR is measured by the mitutoyo surface roughness tester. TW was measured by optical tool maker's microscope with image optic plus version 2.0software designed to run under Microsoft widow's 32 bit system which can be captured by the area of the TW. The experiments are planned using Taguchi's orthogonal array in the design of experiments, which helps in reducing the number of experiments. The experiments were conducted according to orthogonal array. The three cutting parameters selected for the present investigation is cutting speed, feed and depth of cut. Since the considered factors are multi-level variables and their outcome effects are not linearly related, it has been decided to use three level tests for each factor. The machining parameters used and their levels chosen are given in Table-2. Taguchi's orthogonal array of L_{27} is most suitable for this experiment. This needs 27 runs and has 26 degrees of freedoms. It can conduct three levels of parameters. To check the degrees of freedom (DOF) in the experimental design, for the three levels test, the three main factors take 6 (3× (3-1)) DOFs. Square effects and interaction between parameters take the remaining DOFs. The values of machining parameters and S/N ratio for SR are presented in Table-3.

Minitab14 statistical software has been used for the analysis of the experimental work. The software studies the experimental data and then provides the calculated results of signal-to-noise ratio. In this work, the software has given the signal-to-noise ratio for both the SR and TW. The effect of different process parameters on TW and SR are given in Tables 4 and 5, respectively. The main effect plot for S/N ratio for SR and TW are shown in Figure-2 and Figure-3. From the figure process parameters changes from one level to another. The average value of S/N ratio has been calculated to find out the effects of different parameters and their levels. In addition, a statistical ANOVA was performed to see those process parameters that significantly affect the responses. The experimental results were analyzed with ANOVA which is used for identifying the factors which significantly affecting the performance measures. The results of the ANOVA with SR and TW are shown in Tables 6 and 7, respectively. This analysis was carried out for significance level of $\alpha = 0.05$, i.e., for a confidence level of 95%.

Table-2. Machining parameters and levels.

Process parameter	Process designation	Level 1	Level 2	Level 3
Cutting speed (m/min)	A	110	160	210
Feed (mm/rev)	B	0.1	0.2	0.3
Depth of cut (mm)	C	0.7	1.4	2.1

Table-3. Experimental results for SR and TW.

Trial	A	B	C	SR (μm)	S/N for SR	TW (μm)	S/N for TW
1	110	0.1	0.7	0.64	3.87	170.51	-44.63
2	110	0.1	1.4	0.61	4.29	207.34	-46.33
3	110	0.1	2.1	0.56	5.03	218.85	-46.80
4	110	0.2	0.7	1.39	-2.86	237.06	-47.49
5	110	0.2	1.4	1.14	-1.13	223.65	-46.99
6	110	0.2	2.1	1.11	-0.90	201.28	-46.07
7	110	0.3	0.7	1.66	-4.40	234.08	-47.38
8	110	0.3	1.4	1.44	-3.16	192.34	-45.68
9	110	0.3	2.1	1.02	-0.17	241.54	-47.65
10	160	0.1	0.7	1.49	-3.46	222.15	-46.93
11	160	0.1	1.4	0.92	0.72	171.48	-44.68
12	160	0.1	2.1	0.7	3.09	180.56	-45.13
13	160	0.2	0.7	1.33	-2.47	235.57	-47.44
14	160	0.2	1.4	1.43	-3.10	226.62	-47.10
15	160	0.2	2.1	1.38	-2.79	251.97	-48.02

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16	160	0.3	0.7	1.17	-1.36	210.24	-46.45
17	160	0.3	1.4	1.23	-1.79	269.86	-48.62
18	160	0.3	2.1	1.33	-2.47	268.37	-48.57
19	210	0.1	0.7	1.83	-5.24	216.19	-46.69
20	210	0.1	1.4	0.64	3.87	217.68	-46.75
21	210	0.1	2.1	0.74	2.61	220.7	-46.87
22	210	0.2	0.7	1.51	-3.57	265.39	-48.47
23	210	0.2	1.4	1.43	-3.10	281.8	-48.99
24	210	0.2	2.1	1.23	-1.79	277.33	-48.85
25	210	0.3	0.7	1.7	-4.60	234.08	-47.38
26	210	0.3	1.4	1.47	-3.34	226.62	-47.10
27	210	0.3	2.1	1.39	-2.86	252.01	-48.02

Table-4. Taguchi analysis: SR versus A, B, C.

Level	A	B	C
1	0.06220	1.64526	-2.68090
2	-1.51796	-2.41895	-0.75213
3	-2.00636	-2.68843	-0.02909
Delta	2.06856	4.33369	2.65180
Rank	3	1	2

Table-6. Analysis of Variance for SR.

Source	DF	SS	MS	F	P
A	2	0.315	0.15790	2.62	0.098
B	2	1.226	0.61338	10.17	0.001
C	2	0.635	0.31774	5.27	0.015
Error	20	1.206	0.06034		
Total	26	3.384			

Table-5. Taguchi analysis: TW versus A, B, C.

Level	A	B	C
1	-46.56	-46.09	-46.99
2	-47.00	-47.72	-46.92
3	-47.69	-47.43	-47.34
Delta	1.12	1.63	0.42
Rank	2	1	3

Table-7. Analysis of Variance for TW.

Source	DF	SS	MS	F	P
A	2	3943.0	1971.5	3.87	0.038
B	2	8819.3	4409.6	8.65	0.002
C	2	620.6	310.3	0.61	0.554
Error	20	10190.6	509.5		
Total	26	23573.5			

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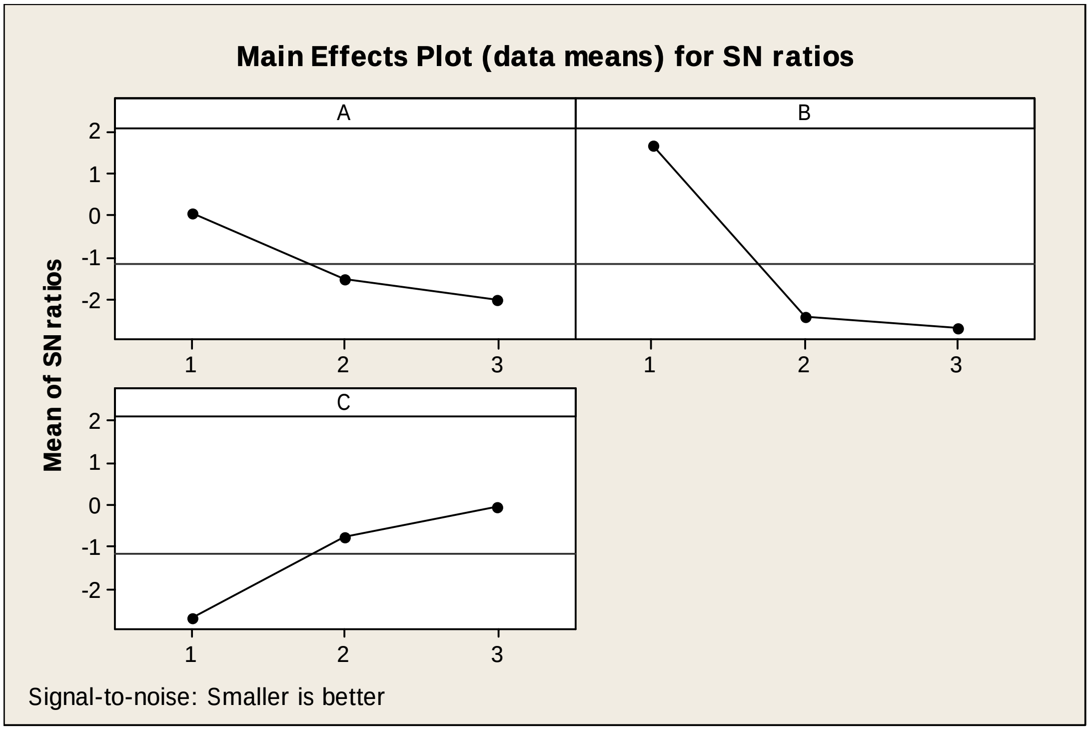

Figure-2. The Main effect of plot for S/N ratio for of SR.

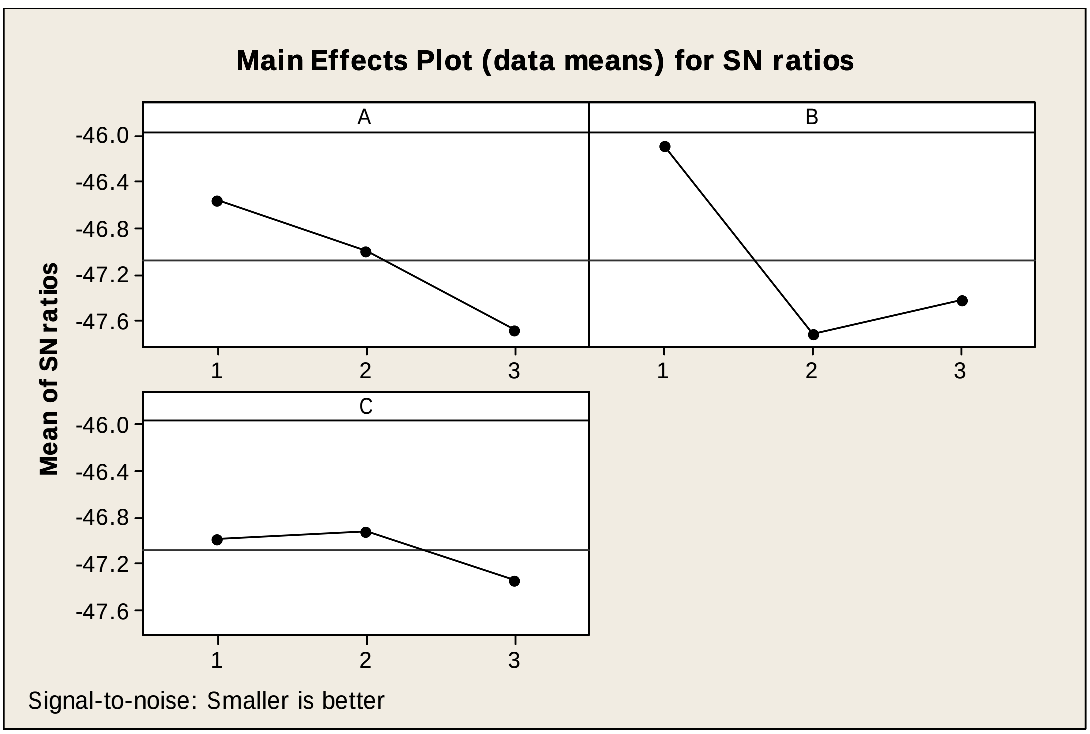

Figure-3. The Main effect of plot for S/N ratio for of TW.

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4. RESULTS AND DISCUSSIONS

4.1 Optimal setting of machining parameters

The measured values of SR and TW for the machined surfaces are corresponding to all the experimental runs are given in Table-3. Signal to noise ratio: Analysis of the influence of each control factor (A, B and C) on the roughness SR and TW has been performed with a so-called signal to noise ratio of response Table. Response Tables of S/N ratio for SR and TW are shown in Table-4 and Table-5 respectively. It shows the S/N ratio at each level of control factor and how it is changed when settings of each control factor are changed from one level to another. The influence of each control factor can be more clearly represented with response graphs Figure-1 and Figure-2. The slope of the line which connects between the levels can clearly show the power of the influence of each control factor. According to the rank value for Table-4 for each control factor that the feed rate has the strongest influence on SR followed by depth of cut and cutting speed. Similarly from Table-5 it can be seen that the feed rate had the strongest influence on tool wear followed by cutting speed and then by depth of cut. From the main effects the plot for S/N ratio for SR is in Figure-1, the SR appears to be an almost linear increasing function of feed rate and decreasing function of depth of cut. Thus in order to reduce the level of SR, Feed rate should be set to its lowest level (0.1mm/rev) and depth of cut to its highest level (2.1mm). Also, high level (210m/min) or low level (110m/min) of cutting speed, may be preferred, while the effect of cutting speed has not been found statistically significant (p-value = 0.98). The main effects of plot for TW at the highest feed rate and high cutting speed of the TW is increased.

From Table-6 ANOVA for SR. It can be found that depth of cut and feed rate are the significant cutting parameters for affecting SR. The change of the cutting speed range given in Table-3 has an insignificant effect on SR (p-value = 0.98). Therefore, based on S/N and ANOVA analysis, the optimum cutting parameters for SR are the feed rate at level 1, the cutting speed at level 1, and depth of cut at level 3. From Table-7, ANOVA for TW. It can be found that cutting speed and feed rate are the significant cutting parameters for affecting TW. The change of the depth of cut range is given in Table-4 has an insignificant effect on TW (p-value = 0.554). Therefore, based on S/N and ANOVA analysis, the optimal cutting parameters for TW are the feed rate at level 1, the cutting speed at level 1, and depth of cut at level 2.

4.2. Prediction of SR and TW

4.2.1 Training of artificial neural network

The training of the ANN with error BB training algorithm for 20 input–output patterns has been performed using NN toolbox in MATLAB 7.9.0 software. In the current study, multi-layer feed forward ANN three neurons in the input layer and one hidden layer with ten neurons were considered to estimate TW and SR of turning process. The network configuration as 3×10×2 was constituted, and it was saved during the determination of training parameters. The ANN training simulation was carried out using the variable learning rate training procedure of the 'MATLAB' NN toolbox. Maximum number of iteration or epochs=1000.The variation for number of iteration is shown in Figure-4. From the Figure performance is 3.0477_e^{-006}.

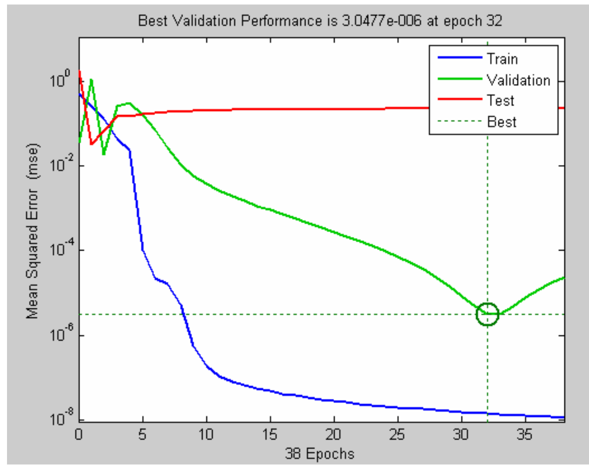

Figure-4. The variation of mean squared error with the number of epochs.

4.2.2 Testing of artificial neural network

After the ANN was trained firstly, the test phase is started by presenting seven input patterns, which were employed for the testing purpose. For each input pattern, the predicted value of SF and TW were compared with the respective measured average values and the absolute percentage error was computed as per given equation (2),

$$\% \text{ Absolute error } (\%Ae) = \frac{y_{exp} - y_{pred}}{y_{exp}} \text{ X } 100 \quad \ldots\ldots (2)$$

Where y_{exp} is the measured value and y_{pred} is the ANN predicted value of the response. It was found that the predicted and experimental values were very close to each other. The correlation coefficient between the targets and predicted output is 1. This means that there was a good correlation between predicted and experimental values. For the validation of the NN, seven input-output patterns were tested, which is not included in the training data set. The data set for validation purpose is given in Table-8. For this data set, the SR and TW values are estimated using the ANN model and then compared with the measured experimental values. The comparisons for the verification data set are shown in Table-8. It is clear that the estimated values show about the same tendency as that of the actual values of TW and SR. The graphical representation of correlation of training and testing patterns are shown in Figures 5 and 6.

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Table-8. Test result of ANN testing patterns.

Trial	A	B	C	SR_{exp}	SR_{pred}	% Ae	TW_{exp}	TW_{pred}	% Ae
1	110	0.2	0.7	1.39	1.39	$7.2e^{-07}$	237.06	237.06	$2.5e^{-07}$
2	110	0.3	1.4	1.44	1.43	0.11	192.34	192.37	0.02
3	160	0.1	2.1	0.7	0.7	$7.14e^{-06}$	180.56	180.57	0.01
4	160	0.3	0.7	1.17	1.17	$3.42e^{-06}$	210.24	210.24	$1.46e^{-05}$
5	210	0.1	1.4	0.64	0.64	0.023	217.68	217.68	$9.4e^{-05}$
6	210	0.2	2.1	1.23	1.27	3.52	277.33	241.77	12.82
7	210	0.3	2.1	1.39	1.39	$1.22e^{-05}$	252.01	252.01	$6.75e^{-07}$

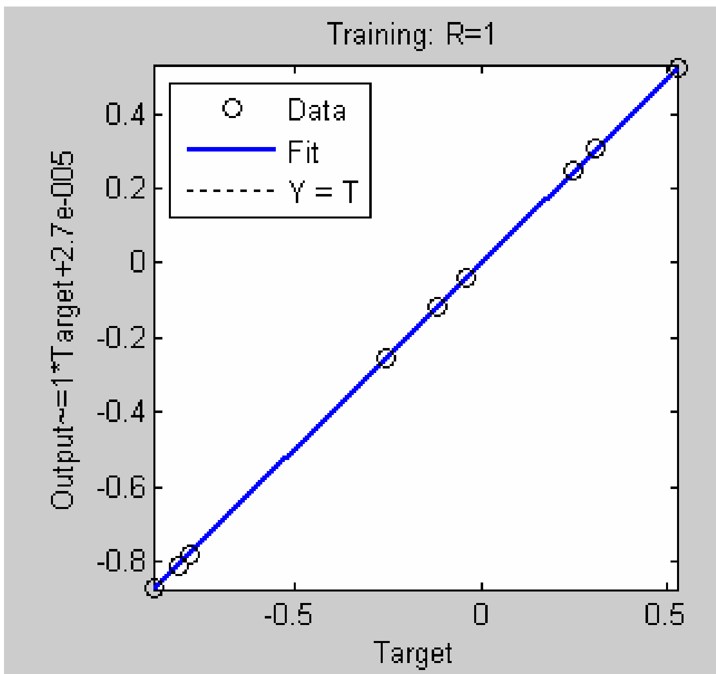

Figure-5. correlation coefficient for training patterns.

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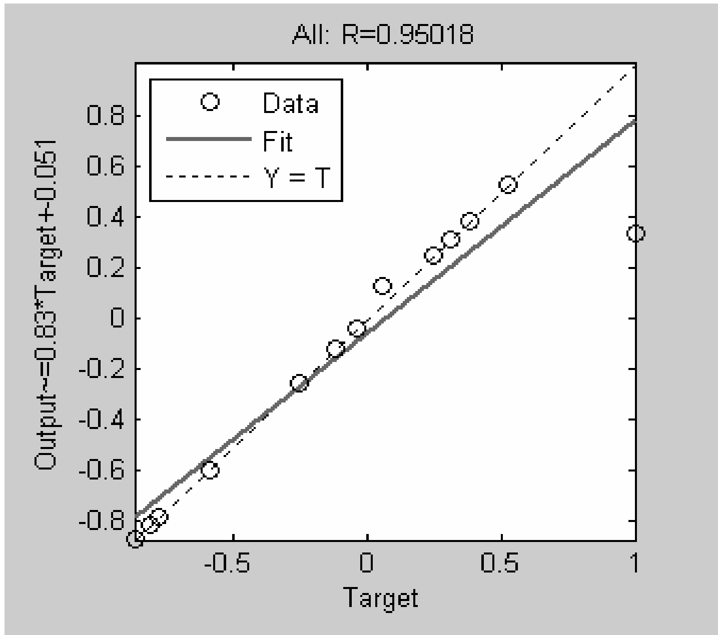

Figure-6. correlation coefficient for testing patterns.

The ANN model developed for the present work can be used to analyze the effects of selected process parameters on TW. The comparison of trained ANN results with the experimental results show reasonably close agreement between experimental and target values and the NN model outputs of the SR and TW. In the design of ANN, desired major concern was to obtain a good generalization capability. Hence, ANN models can predict the response for any new input process parameters with high accuracy. ANN prediction model can be improved by defining more data and number of levels for input parameters, but this requires large number of experiments. There are many factors such as number of hidden neurons, and learning factors that determined by trial and error affect the success of ANN training. In current investigation, a number of hidden neurons and learning factors were found to be optimum such that the present ANN model is trained with 0.01 mean absolute error using 20 training patterns. In confirmation, phase 7 testing data were tested. Although some cutting parameters used in the ANN checking test set were not included and also outside the training set, the neural network acquired nonlinear mappings from the training data and the SR and TW were predicted accurately.

5. CONCLUSIONS

The current investigation is focused on optimization, prediction and analysis of CNC turning AISI 316 during change of cutting parameters. From the study of result in turning was using neural network, Taguchi's techniques and ANOVA. The following can be concluded from the present study.

a) Optimum parameter setting for minimization of SR is obtained at a cutting speed of 110 m/min, feed rate 0.1 mm/rev and depth of cut 2.1mm, i.e., $A_1B_1C_3$;
b) Optimum parameter setting for minimization of TW required is obtained at a cutting speed of 110 m/min, feed rate 0.1mm/rev and depth of cut 1.4mm, ie, A1B1C2;
c) The results of ANOVA, the feed rate and depth of cut are the significant cutting parameters for affecting the SR. Similarly the feed rate and cutting speed were the significant cutting parameters for affect TW;
d) It is clear that there are highly non linear relationships between SR and TW with cutting parameters. This situation validates the employing of ANN to develop a model for SR and TW prediction. The results of the NN model show very good agreement between estimated and measured SR and TW; and
e) Therefore, these systems have great potential to predict SR and TW under different conditions. Because of their matching and approximating capabilities, NN are suitable to model the SR and TW patterns.

REFERENCES

[1] Kwok CT., Lo KH, Cheng FT. and Man HC. 2003. Effect of processing conditions on the corrosion performance of laser surface-melted AISI 440C martensitic stainless steel. Surface and Coatings Technology. 166: 221-230.

[2] Liu XL, Wen DH. And Yan G. 2002. Experimental study on turning of hardened Cr15 steel with PCBN tool. J. Mat. Proc. Techn. 129: 217-221.

[3] Thamizhmanii S., Saparuding S. and Hasan S. 2007. Analyses of surface roughness by turning process using Taguchi method. J. Ach. Mat. Manuf. Eng. 20: 503-506.

[4] Abou-El-Hossein K.A. and Yahaya Z. 2005. High speed end milling of AISI 304 stainless steel using new geometrically developed carbide inserts. Proceedings of the 13th International Science Conference. Ach. Mech. Mat. Eng. AMME. Gliwice-Wisa. pp. 1-6.

[5] Trent EM. 1989. Metal cutting. London, Butterworths Press. New York.

[6] Paro J., Hanninen H. and Kauppinen V. 2001. Tool wear and machinability of X5 CrMnN18 18stainless steels. J. Mat. Proc. Techn. 119: 14-20.

[7] Sarwar M., Zhang X. and Gillibrand D. 1997. Performance of titanium nitride coated carbide tipped circular saws when cutting stainless steel and mild steel. Surf. Coat. Technol. 94: 617-21.

[8] DeGarmo EP., Black J.T. and Kohser R.A. 1997. Materials and processes in manufacturing. New Jersey: Prentice-Hall Inc.

[9] Karabuk ZKU. 2006. Machining of austenitic stainless steel using CVD multilayer coated carbide tool. Ciftci/Tribology international. 39: 565-569.

[10] Nikolaos I., Galanis D. and Maolakos E. 2010. Surface roughness prediction in turning of femoral head. Int. j. adv. manuf. technol. 51: 79-86.

[11] Bonnet C., Valiorgue F., Rech J., Bergheau JM., Gilles P. and Claudin C. 2008. Development of a friction modeling method in dry cutting of AISI 316L austenitic stainless steel. Int. j. master. form. suppl. 1: 1211-1214.

[12] Ross J. 1996. Taguchi techniques for quality engineering, McGraw Hill, Singapore.

[13] Ersan Aslan., Necip Camuscu. and Burak Birgoren. 2006. Design optimization of cutting parameters when turning hardened AISI 4140 steel TiCN+Al_2O_3 with mixed ceramic tool. oi:10.1016/j.matdes.2006.02.006.

[14] Ross PJ. 1996. Taguchi techniques for quality engineering: loss function, orthogonal experiments, parameter and tolerance design. 2nd ed. McGraw-Hill, New York.

[15] Ghani JA., Choudhury IA. and Hasan HH. 2004. Application of Taguchi method in the optimizations of end milling operations. J. Mat. Proc. Tech. 145: 84-92.

[16] Ghosh N., Ravi YB, Mukhopadyay S., Paul S. and Mohanty AR. 2005. Estimation of tool wear during CNC milling using neural network-based sensor fusion. doi:10.1016/j.ymssp.2005.10.010.

[17] Chen JC. and Black JT. 1997. A fuzzy-net in process systems for tool-breakage monitoring in end-milling operations. Int. J. Mach. Tool. Manuf. 37: 783-800.

[18] Kosko B. 1994. Neural networks and fuzzy systems, Prentice- Hall of India, New Delhi.

[19] Schalkoff RB. 1997. Artificial neural networks, McGraw-Hill, Singapore.