Soft Modeling Approach in Predicting Surface Roughness, Temperature, Cutting Forces in Hard Turning Process Using Artificial Neural Network: An Empirical Study

Navriti Gupta[1(✉)], A. K. Agrawal[1], and R. S. Walia[2]

[1] DTU, Delhi 110042, India
navritiguptadtu@gmail.com
[2] On Lien, PECTU, Chandigarh, India

Abstract. Hard Turning means turning of steel having hardness more than 50 HRC (Rockwell Hardness C). It is used for metal removal from hardened steels or difficult to machine steels. In this research hard turning of EN-31 steel (tool steel) 48 HRC was done with Carbon Nano Tubes based coated insert and two tools. Taguchi L27 orthogonal array was used for design of experiments. The input parameters taken in this research were cutting speed, feed, depth of cut, type of coating and cutting conditions. The output responses were surface roughness, temperature and cutting forces. 5-5-1 Feed forward artificial neural network was used in simulation of actual cutting conditions and prediction of responses before actual machining was done. The simulation results of ANN were in unison to those predicted by actual experimental procedure. It was concluded that relative error in values of surface finish, temperature and cutting forces as predicted with ANN versus those achieved during experimental procedure were 1.04%, 2.889% and 1.802% respectively, which were very close to actual values.

Keywords: Hard turning · Soft modeling · Carbon Nano tubes · ANN · Feed forward · Surface roughness · Temperature · Cutting force · Relative % error

1 Introduction and Literature Review

Hard turning means turning of steels having hardness more than 50 HRC [1]. Hardened steels find their usage in several industries as tool and die, heavy machine parts and automobile components. Hard turning is rapidly emerging as promising field of machining of hardened steel. It is rapidly replacing grinding as the material removal method from hard steel, due to added advantages as higher material removal, closer tolerances, higher doc, complex shape and sizes of the component [2].

Surface roughness (SR) is one of the important outcomes of the process [3]. It greatly depends on the temperature at tool tip while machining. The adverse conditions in hard turning can be addressed through temperature predictive model. Many researchers have applied different models of outcome response prediction using different control parameters. In earlier research [4] SR of AISI 304 stainless steel

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specimen using multi-layer coated cutting tool was studied using integrated adaptive neuro-fuzzy particle swarm optimization (PSO). In another research [5] minimum surface roughness was predicted using Artificial Neural Network (ANN) and Genetic Algorithm (GA) integrated methodology. In another research [6] tool wear estimation was done using ANN approach. In a separate research [7] turning of D2 steel was done to optimize Temperature in cutting using Taguchi Technique. An important finding was effectiveness of Carbon Nano Tubes (CNTs) based cutting fluid helped in high rate of heat transfer.

ANN model for prediction of SR was presented while CNC turning AISI1030 steel [8]. Another research work elaborated on ANN model in simulation of surface milling of hardened AISI4340 steel with minimal fluid application [9].

In another research machine learning models were applied in determination of SR [10]. The advantage of applying ANN and other machine learning methods in experimental approach is that an idea about yet to be started actual machining process can be achieved. Based on the inhand information, machinist can devise strategies to improve SR and reduce power consumption. The achieved advantages are superior surface finish, low tool temperatures, low wear rate, low cutting forces etc.

2 Materials and Methods

2.1 Experimental Set Up

HMT Centre versatile lathe type 22 is used to carry out the experiments. EN-31 steel (tool steel) is used as work piece material. Bars of diameter 50 mm, length 900 mm are used for turning. Hardness was 48HRC.

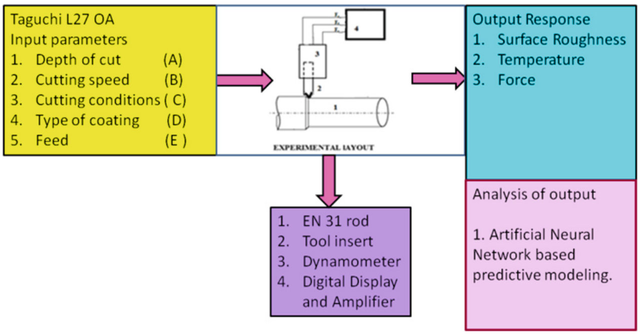

Fig. 1. Block diagram of experiment set up

Figure 1 depicted block diagram of the research conducted. The five input parameters taken in this research were depth of cut, cutting speed, cutting conditions, type of coating and feed. The output responses of experiments were SR, temperature and cutting forces.

In this research three tool bits viz. carbide, carbide + CNTs based Nano coating and Carbide + TiN.

Table 1. Cutting Parameters at different levels

Input parameters	Level		
	1	2	3
A Depth of cut (mm)	0.53	0.81	1.06
B Cutting speed (rpm)	285	480	810
C Cutting conditions	Dry	Wet	Cooled air
D Type of coating	WC	WC + CNT	WC + TiN
E Feed Rate (mm/rev)	0.16	0.19	0.22

Table 1 was showing five different parameters used in the research with their levels.

Scanning Electron Microscopy and Tunnel Electron Microscopy tests were done for characterization of the tool coating.

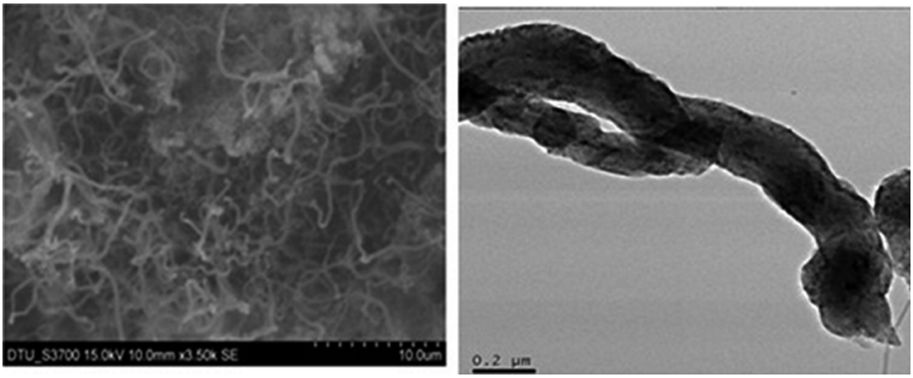

Fig. 2. SEM and TEM images of CNT based Nano coating

Figure 2 depicted SEM and TEM images of carbon Nano tubes based Nano coating. They established the presence of coiled Carbon Nano tubes in the coating. TEM test certified presence of MWCNTs (Multiwalled carbon Nanotubes) in the coating.

2.2 Method: Design of Experiments

Taguchi is well established and efficient approach in design of experiments. It reduces the total number of experiments without actually compromising on the quality of experimental output.

3 Artificial Neural Method

ANN can be used to model any non-linear process as it can approximate any functions more efficiently. Some of unique features are the learning ability, comprehensionability and generalizationability, which enable it to devise highly complex input–output [11, 12]. Accuracy of ANN model is determined by number of neurons, number of hidden layers, weight assigned to hidden layers, learning rate, transfer function and training function. Because of these calculation abilities, ANN is widely finding usage as predictive modeling technique of modeling in with very high accuracy. It expresses the predictive output as Relative % error. The relative % error is found out by calculating the percentage difference between the experimental values and ANN values.

The percentage relative error should be as low as possible. It depicts the deviation of predicted values from the experimental values. The lower % relative error symbolizes accuracy of prediction of responses. Accuracy is dependent on number of neurons and the epoch level selected. The ANN modeling is capable of modeling linear as well as non-linear processes and with higher accuracies than most of the other modeling techniques.

3.1 Artificial Neural Networks: Structure

The structure of artificial network principally consists of different layers of nodes or neurons. Each layer is different or same number of neurons. The input from previous layer node is going to each and every node/neuron in the next layer. This interaction basically is the artificial neural network calculation.

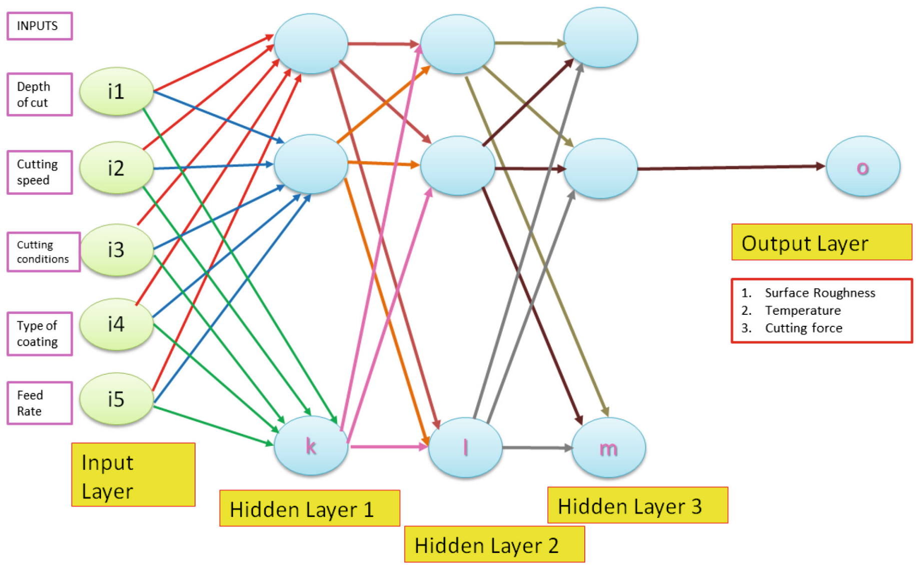

Fig. 3. 5-k-l-m-1 Artificial Neural Network used research

As shown in Fig. 3, a typical neural architecture of 5-k-l-m-1 was shown. It consists of 5 input neurons, k neurons in hidden layer 1, l neurons in hidden layer 2, and m neurons in hidden layer 3. And there was one output layer [13]. Five nodes/neurons in the input layer represents cutting speed v, feed rate f, depth of cut d, cutting condition ct, tool coating type t. Different researchers have used different ANN architectures in their research. In a research [14, 15] different structures of ANN were used and 4–1–1 network structure was labeled as accurate and reliable for the prediction of the SR. However, the good point in ANN is that researchers can choose any number of hidden layers with any number of nodes for each hidden layer [13]. But the general rule is more the number of hidden layers, more the number of node interactions. More the multiple interactions, more is the complexity of the mapping and computation time.

While no. of layers can be decided by taking a glimpse at the past work of researchers in the same field, no of nodes can be decided in accordance with earlier research [16], number of nodes in hidden layer can be approximated as "k/2", "1k", "2k", and "2k + 1" where k is the number of input nodes.

3.2 5-5-1 Feed Forward Network

The ANN calculation was done by nodes present in layer. It involves interaction among the neurons based on complex mathematical calculations. The feedforward type of network takes input and generates output after learning from the training data. The calculations of 5-5-1 feed forward learning type of Neural Network were done in Tiberius standard software of ANN soft prediction.

4 Results and Discussions

4.1 ANN Predicted Values vs. Experimental Values

80–20 training-testing rule is followed in this research. It means model was developed on training of 80% of data. The testing was conducted on 20% of rest data. However, various researchers have attempted using other configurations as 90–10, 70–30 etc. The Epoch of 100 is selected. Epochs are the iterations performed by ANN.

The Table 2 below was giving the absolute relative error between the experimental temperature response and ANN predicted SR, temperature and force response for each experimental run individually.

In Table 2 above the % relative errors between ANN predicted values and actual experimental values were shown for surface roughness and temperature. The numbers of epochs selected were 100. 80–20 training testing model was used. The normalized error values for SR, temperature and force were 0.07754, 0.049757 and 0.061359 respectively, which was less than 0.01. This represents very high accuracy in prediction.

Table 2. Absolute relative error in temperature by ANN Modeling

S. No.	A	B	C	D	E	% Rel error SR	% Rel error Temp	% Rel error Force
1	1	1	1	1	1	−0.01%	−1.06%	−0.53%
2	1	1	2	2	2	6.41%	−0.81%	0.25%
3	1	1	3	3	3	2.95%	0.98%	−3.04%
4	1	2	1	2	2	−1.93%	−1.31%	−0.67%
5	1	2	2	3	3	0.56%	−0.61%	−1.81%
6	1	2	3	1	1	14.22%	−0.98%	−0.88%
7	1	3	1	3	3	−1.17%	−1.26%	3.16%
8	1	3	2	1	1	−3.28%	1.21%	1.39%
9	1	3	3	2	2	1.13%	0.39%	3.77%
10	2	1	1	2	3	1.90%	−2.29%	1.80%
11	2	1	2	3	1	0.96%	−0.29%	−3.35%
12	2	1	3	1	2	−10.31%	−0.12%	−1.63%
13	2	2	1	3	1	−0.28%	−1.46%	0.92%
14	2	2	2	1	2	0.93%	−4.29%	−0.28%
15	2	2	3	2	3	−0.83%	0.86%	2.98%
16	2	3	1	1	2	0.92%	−0.59%	0.62%
17	2	3	2	2	3	−1.58%	0.48%	−5.57%
18	2	3	3	3	1	7.47%	−0.51%	2.73%
19	3	1	1	3	2	0.28%	0.53%	0.42%
20	3	1	2	1	3	0.88%	−0.52%	1.39%
21	3	1	3	2	1	−2.83%	−0.89%	−5.82%
22	3	2	1	1	3	−3.31%	0.50%	−1.04%
23	3	2	2	2	1	4.84%	0.21%	−0.42%
24	3	2	3	3	2	4.16%	0.71%	−0.40%
25	3	3	1	2	1	−0.91%	−3.63%	0.19%
26	3	3	2	3	2	3.18%	−0.46%	2.57%
27	3	3	3	1	3	0.79%	−1.23%	−1.07%
Average error						2.89%	1.04%	1.80%
ANN vs. Experimental								
Epoch				100				
Hidden neurons				5				
Learning rate				80%				
Normalised Error						0.07754	0.049757	0.061359

4.2 Graphical Interpretation of Results

Graphs were plotted for % ge relative error for all of 27 experimental runs for each response of SR, force and temperature. The graphs provide an overall picture of the process.

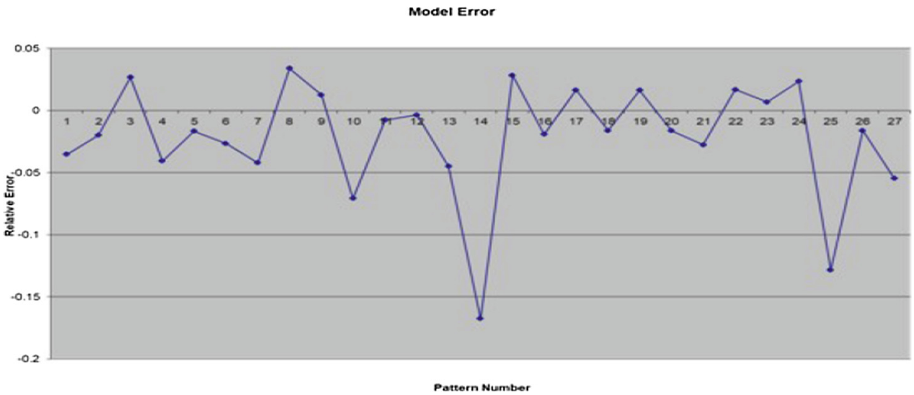

Fig. 4. Model error in Relative error in ANN Modeling value of SR

The Fig. 4 above is graphical representation of % ge relative error in ANN predicted values of SR.

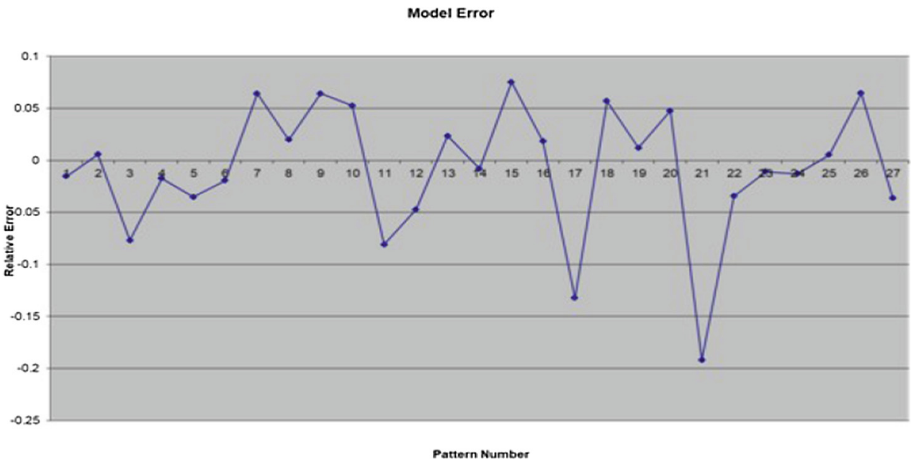

Fig. 5. Model error in Relative error in ANN Modeling value of force

The Fig. 5 above is graphical representation of % ge relative error in ANN predicted values of force.

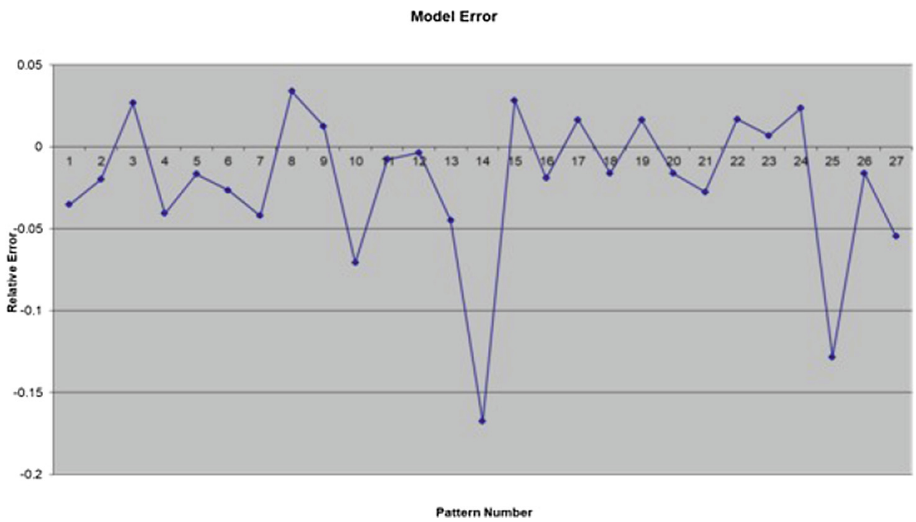

Fig. 6. Model error in Relative error in ANN Modeling value of force

The Fig. 6 above is graphical representation of % ge relative error in ANN predicted values of force.

5 Conclusions

Hard Turning is a versatile advanced metal removal especially in precision tooling machine industries as dies, molds, aerospace etc. The SR is an important indicator of machining performance. It itself is dependent upon various other factors as cutting force, tool tip temperature, wear rate, energy and power consumption, torque on tool etc.

So if advanced prediction of outcomes of machining can be done, it will help in improving the process capability. In this research work, Experiments were performed as per taguchi L27 model to predict SR, temperature and force. And advanced ANN prediction of surface roughness, temperature and force were done. The predicted values vs. the experimental results were in unison to each other.

Table 3. Average relative error in ANN based modeling and experimental investigation

	Temperature	Surface roughness	Force
Average relative error	1.04%	2.889%	1.802%

Table 3 above was summarizing relative error between the predicted value of output response and actual response for Temperature, surface roughness and force.

The error value was in range 0–3%. This clearly shows that the two values were in unison.

ANN network can be helpful in predicting the responses prior to the experiments based on training data. In such case, process improvement will have a greater scope. Such techniques may be indispensable for industries where difficult to machine and hard materials are used as nuclear sector, airplane industry, ship building, Construction, Heavy earthmovers, auto-motive industry etc. Many advanced coatings have been used. In this research, CNTs based Nano coating is used, which is one of the novelties of this research work.

6 Future Scope

1. The optimization with ANN can be used for prediction of output responses. GA (Genetic Algorithm) can be used in conjunction with ANN to find out the optimum cutting conditions for better results. Researchers in mechanical and production engineering fields are not limiting themselves to the older and conventional methods of optimization techniques. Unconventional and modern optimization techniques are being used for testing older results and to arrive at accurate conclusions.
2. Predictive Modeling can be done for cost saving. As simulation results are closer to actual experimental results, process planning can be altered accordingly.
3. Reduction in cost of rejection, as simulation results will give us in sight of actual process.

References

1. Tonshoff, H.K., Arendt, C., Ben Amor, R.: Cutting of hard steel. Ann CIRP **49**, 547–566 (2000)
2. Tonshoff, H.K., Wobker, H.G.: DBrandt: hard turning, Influence on the work piece prop. Trans. NAMRI/SME **23**, 215–220 (1995)
3. Kaladhar, M.: Evaluation of hard coating materials performance on machinability issues and MRR during turning operations. Measurement **135**, 493–502 (2019)
4. Aydın, M., Karakuzu, C., Uçar, M., Cengiz, A., Çavuşlu, M.A.: Prediction of SR and cutting zone temperature in dry turning process of AISI 304 stainless steel using ANFIS with Particle Swarm Optimization learning. Int. J. Adv. Manuf. Technol. **67**, 957–967 (2013)
5. Oktem, H., Erzurumlu, T., Erzincanli, F.: Prediction of minimum surface roughness in end milling mold parts using NN and GA. Mater. Des. **27**(9), 735–744 (2006)
6. Kaya, B., Oysu, C., Ertunc, H.M.: Force–torque based on-line tool wear estimation system for CNC milling of Inconel 718 using NN. Adv. Eng. Softw. **42**, 76–84 (2011)
7. Sharma, P., Sidhu, B.S., Sharma, J.: Investigation of effects of nanofluids on turning of AISI D2 steel using MQL. J. Clean. Prod. **108**, 72–79 (2015)
8. Nalbant, M., Gökkaya, H., Ihsan Toktaş, G.S.: The experimental investigation of the effects of uncoated, PVD- and CVD-coated cemented carbide inserts and cutting parameters on surface roughness in CNC turning and its prediction using artificial neural networks. Robot. Comput. Integr. Manuf. **225**, 211–223 (2009)

9. Leo, K., Wins, D., Varadarajan, A.S.: Prediction of surface roughness during surface milling of hardened AISI 4340 steel with Minimal cutting fluid application using Artificial Neural Network. Int. J. Adv. Prod. Eng. Manag. **7**(1), 51–609 (2012)
10. Çaydaş, U., Ekici, S.: Support vector machines models for surface roughness prediction in CNC turning of AISI 304 austenitic stainless steel. J. Intell. Manuf. **23**(3), 639–650 (2012)
11. Kosko, B.: Networks and Fuzzy Systems. Prentice-Hall of India, New Delhi (1994)
12. Schalkoff, R.B.: Artificial Neural Networks. McGraw-Hill International Edition. McGraw-Hill, New York (1997)
13. Kant, G.: Prediction and optimisation of machining parameters for minimizing surface roughness and power consumption during turning of AISI1045 Steel (2016)
14. Sanjay, C., Jyoti, C.: A study of surface roughness in drilling using mathematical analysis and neural networks. Int. J. Adv. Manuf. Technol. **29**, 846–852 (2006)
15. Sanjay, C., Jyoti, C., Chin, C.W.: A study of surface roughness in drilling using mathematical analysis and neural networks. Int. J. Adv. Manuf. Technol. **30**, 906 (2006)
16. Zhang, G., Patuwo, B.E., Hu, M.Y.: Forecasting with artificial neural networks: the state of the art. Int. J. Forecast. **14**(1), 35–62 (1998)