# Optimization of Process Parameters in Turning Operation of AISI-1016 Alloy Steels with CBN Using Artificial Neural Networks

K.Mani lavanya[1], R.K.Suresh[2],A.Sushil Kumar Priya[3],G.Krishnaiah[4].

*[1]PG Scholor, [2]Asst. Professor (Sr), Department of Mechanical Engineering, Srikalahasteeswara Institute of Technology, Srikalahasti.[3]Head Department of Mechanical Engineering,Govt Polytechnic college,Kavali.[4]Head, Department of Mechanical Engineering, S.V.U College of Engineering,S.V University,Tirupati.*

***Abstract*—.We report the development of a predictive model based on artificial neural network (ANN) for the estimation of Surface roughness of AISI-1016 during orthogonal turning with CBN insert tool. Turning experiments were conducted at different cutting conditions on a PSG-A141 conventional lathe using CBN uncoated insert as tool with ISO designations SNMG - 120408 and AISI-1016 as work piece using full factorial design. Cutting speed (*v*), feed rate (*f*), depth of cut (*d*), were the input parameters of the machining experiment as well as the ANN prediction model while the Surface roughness (Ra) was the output variable. The neural networks with feed-forward and back-propagation learning algorithms were designed using the MATLAB Neural Network Toolbox. An optimal ANN architecture with the Levenberg-Marquardt training algorithm and a learning rate of 0.1 was obtained using Taguchi method of experimental design. With the optimized ANN architecture, parametric study was conducted to relate the effect of each turning parameters on the surface roughness.The results obtained conclude that ANN is reliable method and it can be readily applied to different metal cutting processes with greater confidence.**

***Keywords*— Model, ANN, CBN inserts, Taguchi method, AISI-1016 steel, Turning**

## I. INTRODUCTION

The surface quality is an important parameter to evaluate the productivity of machine tools as well as machined components. Hence, achieving the desired surface quality is of great importance for the functional behavior of mechanical parts. Surface roughness is used as the critical quality indicator for the machined surfaces and it affects the several properties such as wear resistance, fatigue strength, coefficient of friction, lubrication, heat transmission, wear rate and corrosion resistance of the machined parts. Today every manufacturing industry, special attention is given to dimensional accuracy and surface finish. Thus, measuring and characterizing the surface finish can be considered as a predictor for the machining performance.The mechanism behind the formation of surface roughness is very dynamic, complicated, and process dependent [1]. Surface roughness in turning process has been found to be influenced in varying amounts by a number of factors such as cutting parameters, cutting fluid, and workpiece hardness [2]. Many investigations on surface roughness of various metallic materials have been carried out but very few on soft materials such as polymers. The polymers require machining operations at the final assembly stage in order to get the finished components, even though they are produced as near net shapes [3]. Nevertheless, the knowledge regarding the machining of polyamides is limited. Hence the machining of polymers often presents challenges to engineers in terms of close tolerances, their unusual geometry, and softness, which means that it behaves differently as compared with conventional metal cutting [4]. Among various types of polymers, the polyamides have attracted a great deal of interest over the last few years. Modeling the correlation between cutting parameters and process parameters in machining of polyamides is of prime interest. Besides traditional empirical modeling using regression analysis (RA), the artificial neural network (ANN) based modeling is increasingly becoming popular. To ensure the quality of machining products, and to reduce the machining costs and increase the machining effectiveness, it is very important to select the optimal machining parameters [5]. The selection of cutting tool and process parameters is very much essential in machining of polymers [6]. In machining practice, most of the time the optimal cutting conditions are determined using Taguchi method and by coupling empirical models based on RA and ANNs with different optimization algorithms. This study was inspired by the very limited work on the application of ANNs in modeling the relationship between cutting parameters and surface roughness during turning of polyamide, as well as determining the optimal cutting conditions for minimizing surface roughness. The surface roughness model was developed in terms of cutting speed, feed rate, depth of cut, and tool nose radius using the data from the turning experiments conducted according to Taguchi's L27 orthogonal array (OA). The optimal cutting parameter settings were determined by applying the harmony search algorithm (HSA) [7] to the developed mathematical model of surface roughness based on ANN.

## II. EXPERIMENTAL WORK

In the present work AISI-1016 was machined on PSG-A141 ·Conventional lathe by using a CBN insert tool (SNMG 1204 08). The chemical composition of AISI-1016 is given in Table 1. Taguchi's $L_{27}$ orthogonal array was chosen for the experimental design. Experiments were conducted by varying the cutting parameters and the average surface roughness values (Ra) were measured by using Mituto211 Surf test with a sampling length of 5 mm. The considered cutting parameters and their level are shown in Table 2.

| S.NO | Metal | Range |
|---|---|---|
| 1 | Carbon | 0.36-0.44% |
| 2 | Silicon | 0.10-0.35% |
| 3 | Manganese | 0.45-0.70% |
| 4 | Sulphur | 0.040% |
| 5 | Phosphorous | 0.035% |
| 6 | Chromium | 1.0-1.40% |
| 7 | Molybdenum | 0.20-0.35% |
| 8 | Nickel | 1.30-1.70% |

Table 1 Chemical Composition of AISI-1016 Alloy

In the study, the average surface roughness (*Ra*) was considered. The machined surface was measured around the circumference of the workpiece using the surface profilometer Surftest Mitutoyo SJ-210-P. To develop mathematical model based on ANN that relates the cutting parameters and average surface roughness (*Ra*), a plan of experiment is needed. The classical design of experiment (DOE) is sometimes too complex, time consuming and not easy to use. Hence, in the present investigation, the Taguchi's DOE was applied. Four cutting parameters, namely, cutting speed (*s*), feed rate (*f*), and depth of cut (*d*), were considered. The cutting parameter ranges were selected based on preliminary investigations and previous research by The cutting parameters were arranged in standard Taguchi's L27 Orthogonal Array.

| Machining Parameters | Level-1 | Level-2 | Level-3 |
|---|---|---|---|
| Speed(v) | 360 | 740 | 1150 |
| Feed(f) | 0.05 | 0.1 | 0.13 |
| Depth of cut(d) | 0.5 | 0.75 | 1.0 |

Table 2 Cutting parameters and their levels.

## III ARTIFICIAL NEURAL NETWORK (ANN) MODEL FOR SURFACE ROUGHNESS.

In this work, the input layer has three neurons corresponding to each of the three cutting parameters and one neuron in the output layer corresponding to each of the response parameter . In order to find out the best network architecture, different networks with different number of hidden layers and neurons in the hidden layer were designed and verified; different training algorithm were used; transfer functions in the hidden layer and output layer were changed and observed the generalization capability of the different networks and finally the optimal network was selected to predict surface roughness. The issue of determining the optimum number of hidden nodes is a crucial and complicated one in neuronal model. The most common approach in determining the number of hidden neurons (nodes) is via trial and error. Several rule of thumbs have also been proposed, such as, the number of hidden nodes depends on the number of input patterns and each weight should have at least ten input patterns (sample size). In the case of one hidden layer network, several practical guidelines exist. These include 2n+1, 2n, n/2 where n is the number of input nodes. Lawrence and Fredrick (1998) suggested that the number of hidden neuron = (n1+n2), where n1 and n2 are the number of input and output nodes respectively.

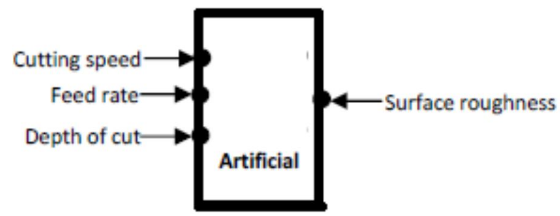


Figure-1:- Schematic diagram of ANN for Ra

For the optimal network architecture, tangent of sigmoid (sigmoid function is of the form f(x) = (1/1+e-x) transfer function 'tansig' has been used in the hidden layer and linear (linear function is of the form f(x) = (x) transfer function 'purelin' has been used in the output layer. The ANN configuration is represented as 3-25-1 that is input layer consists of four input neurons; the hidden layer consists of twenty five neurons and the output layer consisting of four output neurons. The number of neurons in the hidden layer is determined by trial and error method after designing and investigation many networks which vary in their structure, transfer function, training algorithm etc.

Training of an ANN plays a significant role in designing the direct ANN-based prediction. The accuracy of the prediction depends on how well it has been trained. The training of the neural network using a feed-forward back propagation algorithm has been carried out in the work. The network performs two phases of data flow. First the input information is propagated from the input layer to the output layer and, as a result it produces an output. Then the error signals resulting from the difference between the networks predicted values and the actual values are back propagated from the output layer to the previous layers for them to update their weights accordingly. The update of weights continues until the network error goal is reached.

The number of neurons in the hidden layer is intentionally chosen to start with five neuron and hidden neurons are added to the hidden layer incrementally. The addition of hidden neurons continues until there is no significant progress in network performance. The performance of the network was evaluated by mean squared error (MSE) between the experimental and the predicted values for every output nodes in respect of training the network. The feedback from that processing is called the "average error" or "performance". Once the average error is below the required goal or reaches the required goal, the neural network stops training and is, therefore, ready to be verified. MATLAB 7b has been used for training the network architecture which has been developed for prediction of surface roughness.

The training performance of the optimal network (consisting of twenty five hidden neurons) architecture is shown in Figure-4 A computer program was performed under this MATLAB version. The input-output dataset consisting of 27 patterns was divided randomly in two categories: training dataset consist of 75% of the data and test dataset which consist 25% of the data. There are 20 training patterns considered for ANN modeling of surface roughness, After the training, the weights are frozen and the model is tested for validation. In this work, the network is validated in terms of agreement with experimental results.

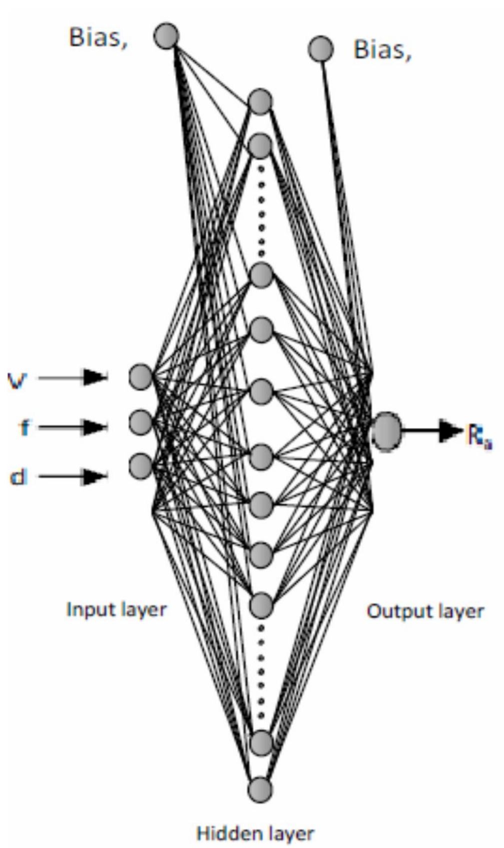


Figure-2:- Proposed ANN Structure

For this purpose, the input parameters to the network are sets of values (in this case 9 Pairs of data set) that have not been used for training the network (raw untrained data) but are in the same range as those used for training. This enables to test the network with regard to its capability for interpolation regarding unseen data.

The Table of 3 show the experimental Ra and ANN computed Ra, values for CBN tool on AISI 1016 material, and it is clear that the values predicted by ANN are very close to the experimental values. Figure-2 shows the ANN prediction values and observed values for the responses surface roughness (Ra) respectively for different test cutting conditions. From the graphs, it is clear that the proposed model can predict values which are nearly very close to experimental observations for each of the output parameters. The results show that the ANN model can be used easily for prediction of surface roughness and hence help in optimum selection of cutting parameters (S, f, d) for the purpose of manufacturing process planning and optimization of machining parameters in turning medium carbon steel (mild steel) by CBN cermet tool.

.

3.1 TEST CONDITIONS AT DIFFERENT HIDDEN NEURONS (CBN Ra)

| cc | v (rpm) | f (mm/rev) | d (mm) | Ra (μm) | ANN Computed $R_a$ (μm) With respect to hidden neurons | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | @20 Neurons | Deviation (%) | @25 Neurons | Deviation (%) | @30 Neurons | Deviation (%) |
| 1 | 1150 | 0.1 | 1 | 2.19 | 2.2492 | -0.0317 | 2.2052 | -0.0116 | 1.9109 | 0.1234 |
| 2 | 740 | 0.1 | 1 | 2.09 | 1.9831 | 0.0557 | 2.3534 | -0.1207 | 2.1048 | -0.0023 |
| 3 | 740 | 0.13 | 0.5 | 2.18 | 2.3229 | -0.1114 | 2.2624 | -0.0825 | 2.4312 | -0.1633 |
| 4 | 740 | 0.13 | 0.75 | 2.08 | 1.9853 | 0.0893 | 2.1184 | 0.0283 | 2.4739 | -0.1348 |
| 5 | 740 | 0.13 | 1 | 2.17 | 2.2143 | -0.0646 | 2.2648 | -0.0888 | 2.387 | -0.1476 |
| 6 | 360 | 0.1 | 0.5 | 2.18 | 2.0024 | 0.0772 | 2.3087 | -0.0639 | 2.4251 | -0.1176 |
| 7 | 360 | 0.13 | 0.75 | 2.1 | 2.0839 | 0.0487 | 2.2967 | -0.0487 | 2.2293 | -0.0179 |
| Average | | | | | | 0.0632 | | -0.3879 | | -0.4601 |

Table-3 Comparision of Roughness values with the Hidden Neurons

EXPERIMENTALLY MEASURED VS ANN COMPUTED Ra (µm) FOR CBN

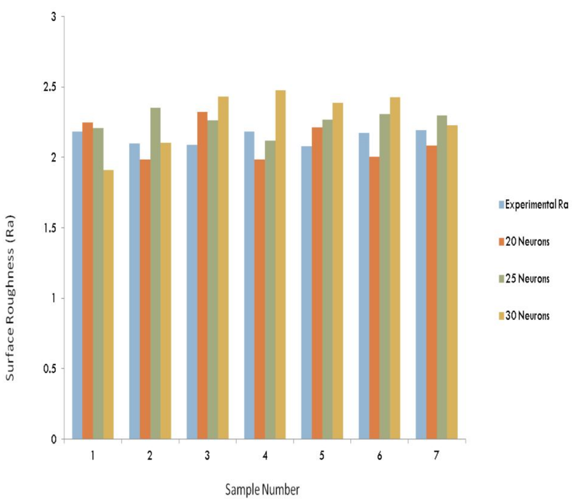


Figure-3:- Comparison of surface roughness at different neurons

ANN TRAINING PERFORMANCE

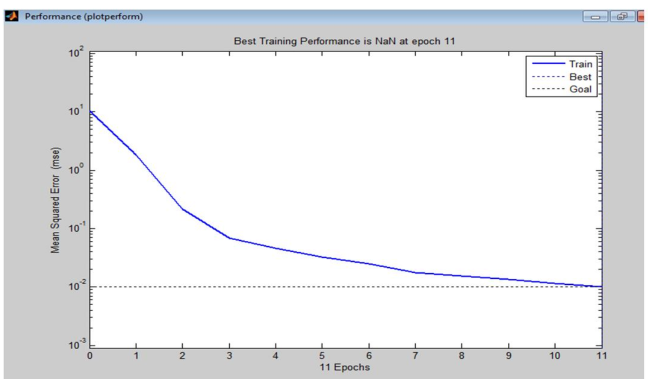


Figure-4:- ANN Training Performance

DATA REGARDING THE FUNCTIONS AND LAYERS

| **Object modeled** | Surface roughness |
|---|---|
| Input neuron | Speed(V), Feed rate (f), Depth of cut (d) |
| Output | Surface roughness (Ra) |
| **Network structure** | |
| Network Type | Feed-forward back-propagation |
| Transfer Function | Transing / Purelin |
| Training Function | Trainlm |
| Learning Function | Learngdm |
| Error Function | Mean square error |
| **Learning conditions** | |
| Learning Scheme | Supervised learning |
| Learning Rule | Gradient decent rule |
| Sample Pattern Vector | 20 (training) , 7(test) |
| Number of hidden layer | One |
| Neurons in hidden layer | 20,25,30 |
| Learning rate | 0.1 |
| Performance goal | 0.001 |
| Minimum epochs | 10000 |

Table-4:- Data Regarding the Functions and Layers

The neural network has been designed with MATLAB 7.1 software. The back propagation algorithm is a gradient decent error-correcting algorithm

## CONCLUSION

In the present study, multiple linear regression model and ANN model has been developed for predicting the surface roughness in turning of AISI-1016 alloy by using the experimental data. The results of the present work are summarized as follows:

- From the multiple linear regression analysis the interaction terms of speed, feed and depth of cut are not significant on the response surface roughness.
- From the sensitivity analysis feed is the most influenced cutting parameter on the surface roughness followed by speed and depth of cut.

## REFERENCES

[1] J. Z. Zhang, J. C. Chen, E. D. Kirby, Surface roughness optimization in an end-milling operation using the Taguchi design method, *Journal of materials processing technology*, Vol. 184, No. 1-3, (2007), pp. 233–239.

[2] F. Kahraman, A. Sagbas, An investigation of the effect of heat treatment on surface roughness in machining by using statistical analysis, *Iranian Journal of Science & Technology, Transaction B: Engineering*, Vol. 34, No. B5, (2010), pp. 591-595.

[3] V. N. Gaitonde, S. R. Karnik, M. Francisco, D. J. Paulo, Taguchi approach for achieving better machinability in unreinforced and reinforced polyamides, *Journal of Reinforced Plastics and Composites*, Vol. 27, (2008), pp. 909-924

[4] V. G. Dhokia, S. Kumar, P. Vichare, S. T. Newman, R. D. Allen, Surface roughness prediction model for CNC machining of polypropylene, *Proceedings of the Institution of Mechanical Engineers Part B-Journal of Engineering Manufacture* Vol. 222, No. 2, (2008), pp. 137-153.

[5] V. Loganathan, A new heuristic optimization algorithm: harmony search, *Simulation*, Vol. 76, No. 2, (2001), pp. 60–68.

[6] O. Zarei, M. Fesanghary, B. Farshi, R. Jalili Saffar, M. R. Razfar, Optimization of multi-pass face-milling via harmony search algorithm, *Journal of Materials Processing Technology*, Vol. 209, No. 5, (2009), pp. 2386–2392.

[7] Adeel H. Suhail, N. Ismail, S.V. Wong and N.A. Abdul Jalil [2010], Optimization of Cutting Parameters Based on Surface Roughness and Assistance of Workpiece Surface Temperature in Turning Process, American J. of Engineering and Applied Sciences 3 (1): 102-108, 2010

[8] Adesta Erry Yulian T., Riza Muhammad, Hazza Muataz, Agusman Delvis, Rosehan, Tool Wear and Surface Finish Investigation in High Speed Turning Using Cermet Insert by Applying Negative Rake Angles, European Journal of Scientific Research Vol.38 No.2 (2009): pp.188.