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OPTIMIZATION OF QUALITY ENHANCEMENT OF CNC MACHINING PROCESS BY USING NEURAL NETWORKS AND ANFIS

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ABSTRACT

The Surface roughness prediction method using artificial neural network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) are developed to investigate the effects of cutting conditions during turning of EN8 material. The ANN model of surface roughness parameters (*R*a) is developed with the cutting conditions such as cutting speed, feed rate and depth of cut as the affecting process parameters.

The experiments are planned and totally 27 settings with three levels defined for each of the factors in order to develop the knowledge based system. The ANN training method is used for back-propagation training algorithm (BPTA) and also for training the Adaptive neuro fuzzy inference system (ANFIS). We have compared the Artificial Neural Network and Adaptive neuro fuzzy inference systems.

Keywords—Cutting Parameters, Artificial Neural Network, Parameter optimization, Surface Roughness, Adaptive Neuro Fuzzy Inference System [ANFIS].

I. INTRODUCTION

In recent years various studies have been conducted on the CNC machining process. The aim of CNC machining process is to improve the products quality, productivity and minimize the production cost. To produce good quality products which depends upon the machining parameters. The machining parameters are important factors for improving the products quality.

The surface quality is an important parameter in turning process to evaluate the quality of products and machine tools. Machining parameters without optimization are mainly affecting the surface roughness. Predicting the surface roughness of AISI 1040 steel with the help of artificial neural networks and multiple regressions method and investigation of the effect of input cutting parameters on the surface roughness. The multiple regression models are tested by using the analysis of variance (ANOVA) method. Two different variants are used in Back-propagation algorithm. The multiple regression and neural network-based models are compared with the performance (Asilturk and cunkas, 2011).

To analyze the machinability of AISI 4340 steel with zirconia toughened alumina ceramic inserts using Taguchi and regression methods experiments are conducted based on an orthogonal array L9 with three parameters and three levels. Experiment was also conducted to find out the significance and percentage contribution of each parameters with the help of Analysis of variance (Mandal et al., 2011).

The proper selection of cutting parameters can minimize the noise factors and the response of surface roughness. In this method AISI 1020 medium carbon steel is used as a work piece and to analyze the surface roughness and work piece temperature. Using these results optimal cutting parameters can be selected to measure the optimal cutting parameter for each performance using Taguchi techniques (Adeel et al., 2010).

Before the machining process surface roughness is to be determined using ANN method to predict the surface roughness with different cutting conditions. (Karayel, 2009).

The Surface roughness is an important factor for the turning process. The major optimum cutting parameters are speed, feed and depth of cut. By selection optimal cutting parameters the surface roughness can be minimized. Using Real Coded Genetic Algorithm optimum cutting parameters can be selected(Srikanth and kamala, 2008).

Optimal machining parameters like cutting speed, feed rate and depth of cut have to be selected. Using these parameters the average of surface roughness (Ra) can be investigated. In this method 9SMnPb28k (DIN) is used a as a work piece and cemented carbide inserts with developed the ANN models. Using error back-propagation training algorithm (EBPTA) with the knowledge based artificial neural network training method. To analyze the effect of machining conditions with surface roughness parameters. The proper selection of machining parameters is to produce good surface finish (Davim et al., 2008).

To increase the productivity and reduction of cost is depends upon the optimum selection of cutting conditions. To optimize the complex cutting parameters are using neural network approach. To all-important turning parameters are optimized and this approach is suitable for selection of optimum cutting parameters in turning process (Zuperl and Cus, 2003).

The aim of this paper approach is comparison of artificial neural networks and adaptive neuro fuzzy inference system. To investigate the cutting parameter effects and the machining parameters are like cutting speed, feed rate, and depth of cut. The artificial neural network models are training with tested using back propagation training algorithm (BPTA). To find the performance of EN8 medium carbon steel using artificial neural network and adaptive neuro fuzzy inference system. The proposed model is to predict the surface roughness effectively. The artificial neural network produces good results compare to the Adaptive neuro fuzzy inference system.

II. MATERIALS AND METHODS:

In any turning process we are consider many factors. Mainly the affecting surface roughness factors are such as tool variables, work piece variables, and cutting conditions. Tool variables consist of tool material, nose radius, rake angle, cutting edge geometry, tool vibration, tool point angle, etc., The machining input cutting conditions are speed, feed, and depth of cut and difficult to select the hard turning process parameters. The appropriate cutting condition gives good surface quality.

The experiments have been conducted on straight turning of unalloyed medium carbon steel EN8 on a lathe by a TNMG and VNMG at different speed, feed and depth of cut combinations. The Machining process has been conducted with coolant. The wet conditions under which the machining parametres are speed, feed, depth of cut. The experiments conduct using three different parameters with 27 settings.

A. Proposed ANN and ANFIS Model for Surface Roughness:

The developed ANN model to determine surface roughness in a wet condition. The capability of the ANN model is to generalize unseen data dependents on several factors. These Factors are appropriate selection of input-output parameters, the distribution of the input-output dataset, and the format of the presentation of the dataset to the neural network. Selected input parameters are the significant variables that affect the surface roughness while perform turning operation under wet condition. We consider the input parameters are cutting speed, feed rate and depth of cut. The surface roughness is the output parameter of the model.

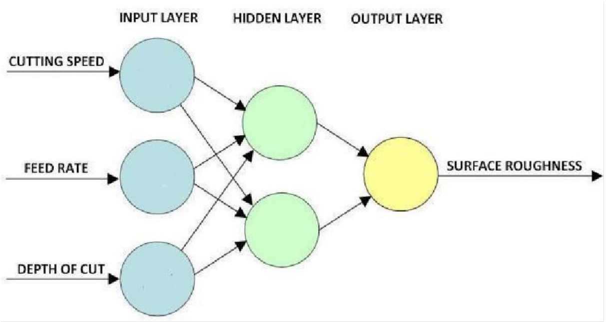

Fig.1 Schematic diagram of ANN for Ra

B. Collection of Input-Output Dataset:

The machining processes have been conducted by straight turning of unalloyed medium carbon steel EN8 on a CNC lathe. By using TNMG and VNMG as an insert at different cutting speeds (V), feed rates (f), depth of cuts (d) under wet condition. After machining each component and the average surface roughness value was also measured by a Kosaka Surf Coder. Thus several pairs of output variables in response to the different combinations of machining input parameters have been obtained.

C. Preprocessing Input – Output Dataset:

The capability of the artificial neural network (ANN) model to generalize regarding unseen data dependents on several factors such as appropriate selection of input-output parameters of the system, the distribution of the input-output dataset, the format of the presentation of the input-output dataset to the neural network. For our ANN model, the input parameters used are the three main machining parameters. The machining parameters are cutting speed, feed rate and depth of cut. The output process parameters are average of surface roughness.

P = {Cutting speed , Feed, Depth of cut}
, T = {Surface Roughness}

In this method several machining tests were carried out and thus 40 pairs of input-output dataset were obtained during the machining trials. Before training the ANN by feeding the dataset to the network and the input-output mapping, one significant task is to process the experimental data into patterns. Training and testing pattern vectors are formed before input output dataset are fed to network. Each pattern is formed with an input condition vector (Pi) and the corresponding target vector (Ti), which is shown in the matrix. Before training the network, the input output dataset were normalized within the range of -1 to +1 using the MATLAB command 'mapminmax'.

D. Experimental setup:

Collecting the data sets are from experiments conducted on a CNC lathe machine in the industry, Chennai, India. The machining experiments details are given in Table 1. Two inserts are used in the EN8 machining experiments. In this experiment totally 27 settings. In Each settings to produced three components. After the each turning process to measure the surface roughness(Ra) was measured with Kosaka Surf coder testing machine. A program was developed using Matlab7.11 software. The surface roughness measurements were taken one time for each work piece. The outputs are measured as 27*3 = 81 samples and their average values are taking as data. In this method EN8 material is a work piece. It is hardened to 50 - 55 HRC, and then normalization. Tensile properties can vary but are usually between 500-800 N/mm2. The specimen was cylindrical bar with 25.5 mm diameter and 26 mm length.

Table 1
Input cutting Parameters with their three levels

Parameters	Level 1	Level 2	Level 3
Cutting Speed (Rpm)	1100	1300	1500
Feed rate (mm/rev)	0.1	0.2	0.3
Depth of Cut (mm)	0.2	0.4	0.6
Work piece Material	C = 0.35 – 0.45	Mn = 0.60 – 1.00	Si = 0.10 – 0.35
	P = 0.05	S = 0.05	

The experiments have been conducted on LML Lokesh Fanuc series Oi – TB lathe. The insert tool TNMG and VNMG is a commercial product available by Ceratizit Company. The cutting parameters were selected to that the measured cutting forces. The suggested input cutting parameters values are shown in Table 1. The cutting conditions unchanged and all experiment was conducted with two inserts with two different operations. The experiments conducted on with coolant and totally 27 different settings using to conduct the experiments were performed according to full factorial design. The surface roughness parameters are generally depends on the input cutting parameters. like cutting speed, feed rate, depth of cut machining tool and cutting tool rigidity. In this method the three main input cutting parameters was selected. The input cutting parameters are cutting speed (V), feed (f), and depth of cut (d). The EN8 material experimental datas and Diameter and Surface roughness average values are shown in Table 2.

Table 2
The Experimental datas with their machining parameters.

Test No :	V (Rpm)	f (mm/rev)	a (mm)	Diameter (mm)	Surface Roughness (Ra)
1.	1100	0.1	0.2	10.83	2.05
2.	1100	0.1	0.4	10.83	2.12
3.	1100	0.1	0.6	10.84	2.55
4.	1100	0.2	0.2	10.88	4.66
5.	1100	0.2	0.4	10.89	4.55
6.	1100	0.2	0.6	10.88	4.96
7.	1100	0.3	0.2	10.91	8.59
8.	1100	0.3	0.4	10.91	9.24
9.	1100	0.3	0.6	10.89	9.72
10.	1300	0.1	0.2	10.80	2.14
11.	1300	0.1	0.4	10.84	2.17
12.	1300	0.1	0.6	10.81	2.87
13.	1300	0.2	0.2	10.84	4.56
14.	1300	0.2	0.4	10.84	4.94
15.	1300	0.2	0.6	10.86	4.59
16.	1300	0.3	0.2	10.90	9.13
17.	1300	0.3	0.4	10.90	8.41
18.	1300	0.3	0.6	10.89	10.23
19.	1500	0.1	0.2	10.84	2.00
20.	1500	0.1	0.4	10.81	3.16
21.	1500	0.1	0.6	10.80	2.03
22.	1500	0.2	0.2	10.85	3.95
23.	1500	0.2	0.4	10.86	4.69
24.	1500	0.2	0.6	10.85	4.53
25.	1500	0.3	0.2	10.90	7.91
26.	1500	0.3	0.4	10.91	9.32
27.	1500	0.3	0.6	10.89	9.64

III. RESULTS AND DISCUSSION:

In this section, the results obtained from the artificial neural networks and Adaptive neuro fuzzy inference system are compared and discussed.

3.1 Artificial neural network:

Multilayer perception structure that is a kind of feed-forward ANNs was applied to model and predict the surface roughness in turning operations. The experimental data presented in Table 2were utilized to build the ANN model. The back-propagation training algorithms, the Gradient descent method and Levenberg – Marquardt (LM), were used for ANNs training. The best results were obtained with this algorithm compared to other training algorithms. Two ANNs structure, 3-2-1 and 3-3-1, were tested. The meaning is 1 node is a output layer, 2/3 node hidden layer, and 3 node input layer for input variables. The neural networks software was coded using the Mat lab 7.11 Neural Network Toolbox. The learning parameters of the proposed ANN structure are presented.

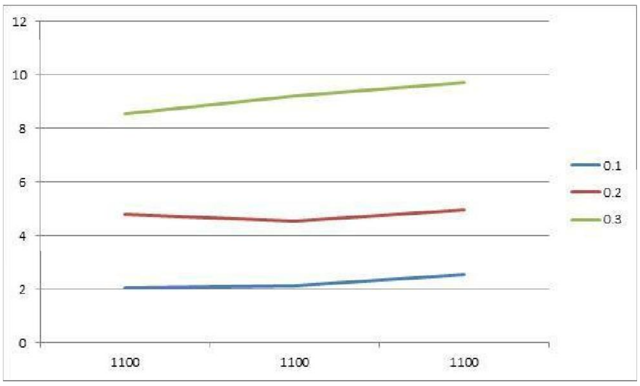

Fig.2. Measured surface roughness values with first level of speed and feed rate. X and Y axis are speed and feed.

The Fig.2. Shows using first level of speed and feed rate (1100 and 0.1, 0.2, 0.3) with the measured surface roughness value. In this graph shows the good surface finish in EN8 material. The cutting parameter ranges are speed 1100 and feed 0.1.

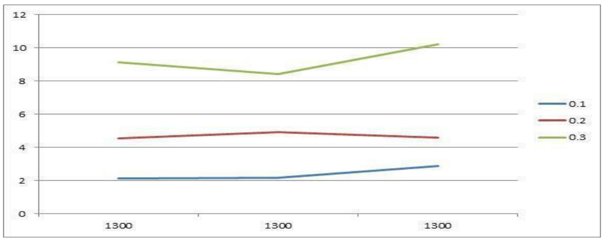

Fig.3. Measured surface roughness values with second level of speed and feed rate. X and Y axis are speed and feed.

The Fig.3 shows using first level of speed and feed rate (1300 and 0.1, 0.2, 0.3) with the measured surface roughness value. In this graph shows the good surface finish in EN8 material. The cutting parameter ranges are speed 1300 and feed 0.1.

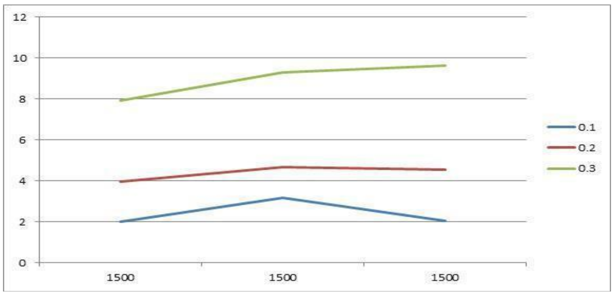

Fig.4. Measured surface roughness values with third level of speed and feed rate. X and Y axis are speed and feed.

The Fig.4. Shows using first level of speed and feed rate (1500 and 0.1, 0.2, 0.3) with the measured surface roughness value. In this graph shows the good surface finish in EN8 material. The cutting parameter ranges are speed 1500 and feed 0.1.

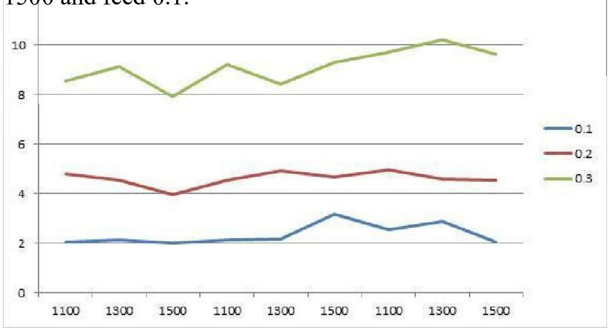

Fig.5 Measured surface roughness values with three different level of speed and Feed rate. X and Y axis are speed and feed.

Fig 5. shows X axis is speed and Y axis is surface roughness. The speed range is 1100 to 1500. And feed rate range is 0.1 to 0.3. The minimum error shows in this graph 1100 and 1500 speed with 0.1 feed rate.

In artificial neural network back propagation training algorithm with mat lab software gives the output values are speed = 1500 rpm , feed = 0.1 mm/rev , depth of cut = 0.2 mm. the percentage of effectiveness = 99%. Using these cutting parameters gives as a input of CNC lathe and to produce the EN8 components and measure the surface roughness value. The ANN surface roughness output shows in Fig.4.The ANN using measured surface roughness values are 2.29 micron.

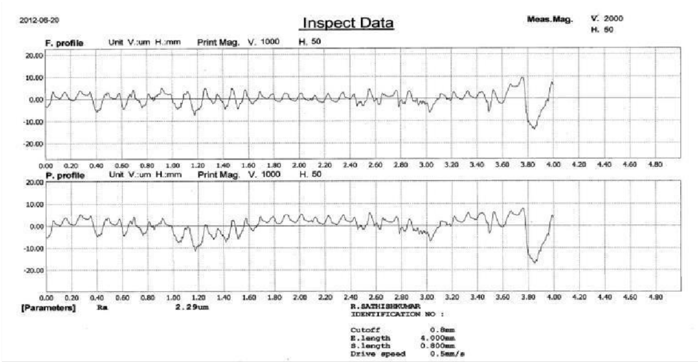

Fig.6. Surface roughness output for Artificial Neural Network.

To measure the surface roughness for pattern plate guide pins with the help of Kosoka surf coder surface roughness testing machine. The ANN Guide pin surface roughness value graph is shown in Fig.6

3.2 Adaptive neuro fuzzy inference system:

In Adaptive neuro fuzzy inference system with mat lab software gives the output values are speed = 1300 rpm, feed = 0.2 mm/rev, depth of cut = 0.6 mm. the percentage of effectiveness = 90%. Using these cutting parameters gives as a input of CNC lathe and to produce the EN8 components and measure the surface roughness value. The ANN using measured surface roughness values are 5.02 micron.

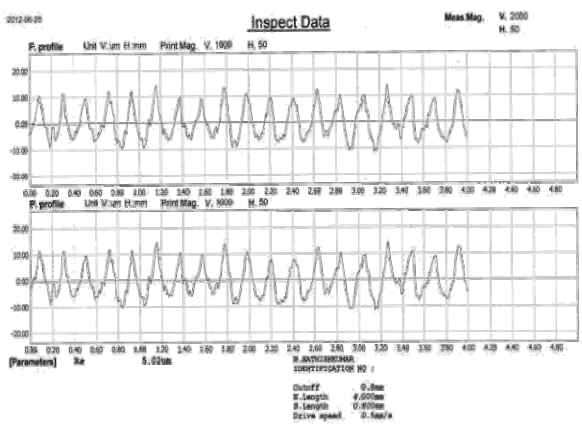

Fig.7. Surface roughness output for Adaptive neuro Fuzzy inference system.

To measure the surface roughness for pattern plate guide pins with the help of Kosoka surf coder surface roughness testing machine. The ANFIS Guide pin surface roughness value graph is shown in Fig.7

3.3 Overall Comparison:

The experimental data set consists of 27 patterns, of which 18 patterns were used for training and testing the performance of the trained network. After the network has successfully completed the training stage, it was tested with the experimental data that were not present in the training data set. The ANN and ANFIS results are compared. The results obtained show that ANN produces the better results compared to Adaptive neuro fuzzy inference system.

IV. CONCLUSION:

In this method, artificial neural network and adaptive neuro fuzzy inference system approaches were used to predict the surface roughness in EN8. The parameters such as cutting speed, feed, and cutting of depth were measured by means of full factorial experimental design. The data obtained were used to develop the surface roughness.

The feed rate is the dominant factor affecting the surface roughness, followed by cutting of depth and cutting speed. The back-propagation training algorithms, the gradient descent method and Levenberg–Marquardt (LM), were used for ANNs training. The best result having the optimization parameters was obtained by Gradient descent method with 2 neurons.

The developed models were evaluated for their prediction capability with measured values. The predicted values were found to be close to the measured values. The proposed models can be used effectively to predict the surface roughness in turning process. The effective percentage is 99% for neural network model, while it is achieved as 90% for adaptive neuro fuzzy inference system.

Considering that advantages of the ANN compared to adaptive neuro fuzzy inference system are simplicity, speed, and capacity of learning, the ANN is a powerful tool in predicting the surface roughness.

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