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Development and investigation of the surface roughness prediction model using ANN in terms of Machining Parameters during the turning of AISI 1040 steel.

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Abstract

Nowadays, surface finish of machined parts plays an important role in manufacturing industry. Poor surface finish invites organization problem seeking identification of the best process condition for the manufacturing process. Surface roughness is the one of the critical performance parameter that has an appreciable effect on several mechanical properties of machined parts such as fatigue behavior, corrosion resistance, creep life, etc. In this present research, an experimental investigation on surface roughness in turning of AISI 1040 steel with coated carbide inserts was carried out. Prediction model for surface roughness in terms of speed, feed and depth of cut is developed using artificial neural network based on gradient descent back-propagation with adaptive learning rate procedure. The predicted values of surface roughness using proposed ANN model have been found to be in close agreement with the experimental data. The correlation coefficient for the entire data set has been found to be 0.982.

1. INTRODUCTION

Turning is the one of the important industrial process which is used to create rotational parts by cutting away unwanted material of metal parts and give the desired shape to the material. The turning is an important process of manufacturing industries. The output quality can be achieved by optimizing the parameters. Optimization of parameters improves output quality and also reduces the manufacturing. Turning parameters are feed rate, cutting speed, depth of cut, cutting fluids and so on.

Surface roughness is the one of the critical performance parameter that has an appreciable effect on several mechanical properties of machined parts such as fatigue behavior, corrosion resistance, creep life, etc. It also affects other functional attributes of machined parts like friction, wear, light reflection, heat transmission, lubrication, electrical conductivity, etc. Hence, achieving the desired surface quality is of great importance for the functional behavior of the mechanical parts.

Turning is a very important machining process in which the unwanted material is removed from the surface of a rotating cylindrical work piece with the help of single point cutting tool. Turning is the machining operation that produces cylindrical parts. In its basic form, it can be defined as the machining of an external surface.

Traditionally the selection of machining parameters is carried out manually based on the experience of the machinist or the planner and the information contained in catalogues and handbooks. Manual selection of machining parameters reflects the problem of variability in experience and judgment among the planners.

2. LITERATURE REVIEW

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R. Kowalszyk et. al. (2015) The outcome of various cutting forces (FF, FP, FC) while machining using PCD tool on sintered carbides WC-Co (25% Co). At a distance of 54mm and with constant depth of cut 0.2 mm every cutting test was conducted using three different inserts of nose radii. The final result which indicated the optimization using algorithm and the control of super hard material during turning was that there was the maximum increase of F_P.

S. Clanknnik et. al. (2014) There is a proposal that one should convert their choice of using optimization technique onto the intelligent methods such like particle swarm optimization or alike optimization. The input parameters considered were cutting speed, feed rate and depth of cut while the response were cutting force, SR & tool life and the optimal combination of parameters was calculated using particle swarm optimization.

D. M. Tati et. al. (2013) This paper proposes a technique called Genetic Algorithm for optimization in order to determine the cutting parameters during machining. While cutting, these parameters play a vital role in reducing the production time and cost and also decides the quality. They concluded that the optimization technique should be such as to ensure maximum product quality and minimum production cost and time.

C. B. Rautara et. al. (2012) They select performance parameter to optimize i.e. SR, by applying optimum cutting parameters while turning of EN8 alloy steel on CNC lathe by coated carbide tool. A second order mathematical order developed for the prediction of SR on giving input parameters using Response Surface Methodology. The optimization of the predict SR is obtained by Genetic Algorithm and validation of results is done by ANOVA.

J. Utoerio et. al. (2012) They used AISI H31 tool steel as work piece which is high in hardness toughness and strength. The DOE is created by using Grey Taguchi technique. A model has been created using residual stresses has an important parameter as this parameter may increase the life of die/mould & their ability to hold out serve mechanical and thermal loading. The optimizations carried out with Artificial Neural Network & Genetic Algorithm.

K. V. Subbaiya et. al. (2012) They used AISI 304 Austenitic Stainless Steel as work piece and turned it on CNC lathe by using PVD coated cremated insert (TiCN-TiN) in order to study the effect of machining parameters i.e. cutting speed, depth of cut, feed rate and nose radii on performance parameters i.e. SR and MRR. Taguchi technique is used to create the prediction model for SR and MRR and the validation of results is done by ANOVA.

R. S. Daas et. al. (2012) Their main motive was to increase the productivity and the quality of the out coming product from the machining process. The work piece used is of AISI D2 Steel and it is turned on CNC lathe in dry condition with machining parameters i.e. cutting speed, depth of cut, feed rate. The performance parameters i.e. minimum tool wear and minimum surface temperature are optimized by developing multiple regression analysis. The DOE is done by Taguchi L9 OA and validation of results is done by ANOVA.

P. Sahu et. al. (2012) AISI 1040 used as work piece for turning with process parameters i.e. cutting speed, depth of cut, feed rate to study the effects on performance parameters i.e. centre line average roughness, root mean square roughness, mean line peak spacing. A three rotatable central composite design has been used for creating mathematical model which predicts SR & Response Surface Methodology has been used for the analysis of the effect that process parameters created on the response. The model was validated by using F-test & its adequacy was done by ANOVA.

K. V. Subbaiya et. al. (2012) The work piece used was AISI 202 Austenitic Stainless Steel for turning with CVD coated tool taking process parameters i.e. cutting speed, feed rate, depth of cut, nose radius. The DOE was done by using full fractional design for optimization of SR. A try has been made by them for developing prediction model for SR and its validation was done by ANOVA.

H. S. Bhidgoliya et. al. (2009) They used Adaptive Neural Fuzzy Intelligent system for creating the prediction model for dry SR. Cutting speed, feed rate and depth of cut are chosen machining parameters and some results are achieved i.e. cutting speed proportional to the SR but feed rate and depth of cut are inversely proportional to the SR.

In the present work the ANN has been selected to investigate the effect of turning parameters on surface roughness. An effort has also been made to develop surface roughness prediction model turning of AISI 1040 steel. Thus objectives and the steps of the present study are:

- Development and investigate of the surface roughness prediction model using Artificial neural network in terms of feed, cutting speed and depth of cut during the turning of AISI 1040 steel.

3. EXPERIMENTAL SETUP

In the present research, CNC Turning Centre PUSHKAR-200 manufacture by HMT is used for the experimentation purpose. It has high power, speed and accuracy and maintain excellent accuracy during the operations.

3.1 **PROCESS PARAMETERS AND LEVEL OF PROCESS PARAMETERS**

In the present work, feed cutting speed and depth of cut were considered as process parameters. The range of these parameters was selected according the literature review and according to range recommended by the cutting tool manufacturer.

TABLE 3.1 Process parameter and their levels

Parameters	Levels		
Feed (mm/rev)	0.1	0.15	0.2
Speed (m/min)	100	150	200
Depth of cut (mm)	0.1	0.2	0.3

The levels were decided according to three level full factorial design. The table 3.1 shows the level of process parameters and table 3.2 shows the complete design matrix for the experimentation according to 3 level full factorial design.

TABLE 3.2 Design matrix for experiments

Exp. no.	Cutting Speed (m/min)	Feed Rate (mm/rev)	Depth of Cut (mm)	Surface roughness (µm)
1	100	0.1	0.1	1.980
2	100	0.1	0.2	2.120
3	100	0.1	0.3	2.220
4	100	0.15	0.1	2.410
5	100	0.15	0.2	2.580
6	100	0.15	0.3	2.660
7	100	0.2	0.1	2.692
8	100	0.2	0.2	2.720
9	100	0.2	0.3	2.890
10	150	0.1	0.1	1.806
11	150	0.1	0.2	1.934
12	150	0.1	0.3	2.025
13	150	0.15	0.1	2.198
14	150	0.15	0.2	2.353
15	150	0.15	0.3	2.426
16	150	0.2	0.1	2.455
17	150	0.2	0.2	2.481
18	150	0.2	0.3	2.636
19	200	0.1	0.1	1.612
20	200	0.1	0.2	1.726
21	200	0.1	0.3	1.808
22	200	0.15	0.1	1.962
23	200	0.15	0.2	2.101
24	200	0.15	0.3	2.166
25	200	0.2	0.1	2.192
26	200	0.2	0.2	2.215
27	200	0.2	0.3	2.353

4. DEVELOPMENT OF ANN MODEL FOR SURFACE ROUGHNESS

The literature review shows mostly researchers used feed forward backpropagation (BP) algorithm and radial basis network algorithm for the development of surface roughness prediction model using ANN but feed forward backpropagation gives accurate results as compare to radial basis network (Zain at el., 2010).

4.1 Normalization of data

The normalization of the input and output data sets is required before feed the data in multilayer feed-forward back-propagation neural network. Normalization is a transformation performed on the data to distribute the same evenly and scale it into an acceptable range for further analysis.

In the present work, normalization of data sets in the range of 0.1 – 1was carried out using the equation as given below

$$N = 0.1 + 0.9\left(\frac{X - X_{min}}{X_{max} - X_{min}}\right)$$

X is the actual value
X_{min} is the minimum value
X_{max} is the maximum value of data
N is the normalized value corresponding to X.

TABLE 4.1 Division of data set for training, testing and validation

Exp no.	Cutting speed (actual)	Cutting Speed (Normalized)	Feed Rate (actual)	Feed Rate (Normalized)	Depth of Cut (actual)	Depth of Cut (Normalized)	Surface roughness (actual)	Surface roughness (normalized)
	m/min	m/min	mm/rev	mm/rev	mm	mm	µm	µm
Training								
1	100	0.1	0.1	0.1	0.1	0.1	1.98	0.359
2	100	0.1	0.1	0.1	0.2	0.55	2.12	0.458
4	100	0.1	0.15	0.55	0.1	0.1	2.41	0.662
7	100	0.1	0.2	1	0.1	0.1	2.692	0.861
8	100	0.1	0.2	1	0.2	0.55	2.72	0.88
9	100	0.1	0.2	1	0.3	1	2.89	1
10	150	0.55	0.1	0.1	0.1	0.1	1.806	0.237
13	150	0.55	0.15	0.55	0.1	0.1	2.198	0.513
15	150	0.55	0.15	0.55	0.3	1	2.426	0.673
16	150	0.55	0.2	1	0.1	0.1	2.455	0.694
17	150	0.55	0.2	1	0.2	0.55	2.481	0.712
18	150	0.55	0.2	1	0.3	1	2.636	0.821
21	200	1	0.1	0.1	0.3	1	1.808	0.238
22	200	1	0.15	0.55	0.1	0.1	1.962	0.347
23	200	1	0.15	0.55	0.2	0.55	2.101	0.444
24	200	1	0.15	0.55	0.3	1	2.166	0.49
25	200	1	0.2	1	0.1	0.1	2.192	0.508
26	200	1	0.2	1	0.2	0.55	2.215	0.524
27	200	1	0.2	1	0.3	1	2.353	0.622
Testing								
5	100	0.1	0.15	0.55	0.2	0.55	2.58	0.782
12	150	0.55	0.1	0.1	0.3	1	2.025	0.391
19	200	1	0.1	0.1	0.1	0.1	1.612	0.1
3	100	0.1	0.1	0.1	0.3	1	2.22	0.528
Validation								
6	100	0.1	0.15	0.55	0.3	1	2.66	0.838
11	150	0.55	0.1	0.1	0.2	0.55	1.934	0.327
20	200	1	0.1	0.1	0.2	0.55	1.726	0.18
14	150	0.55	0.15	0.55	0.2	0.55	2.353	0.622

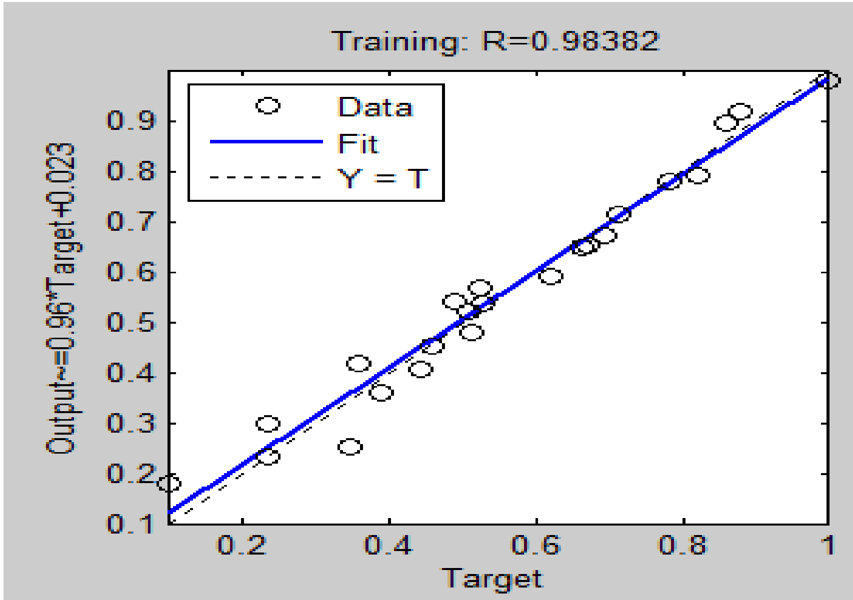

Fig. 4.1. Comparison between the experimental and predicted surface roughness during training

The figure shows two lines i.e. one dash line and other blue line. The dash line shows perfect fit while blue line shows linear fit. The best linear fit between the experimental values and predicted values during training the ANN model is given by the equation as
Predicted value =0.96experimental value +0.023 with 0.9838 regression coefficient which indicates excellent correlation between experimental and predicted values of surface roughness.

4.2 Testing of developed ANN model

The figure shows two lines i.e. one dash line and other red line. The dash line shows perfect fit while red line shows linear fit. The best linear fit between the experimental values and predicted values during testing the ANN model is given by the equation as
Predicted value =0.89 experimental value +0.064 with 0.9905 regression coefficient which indicates excellent correlation between experimental and predicted values of surface roughness.

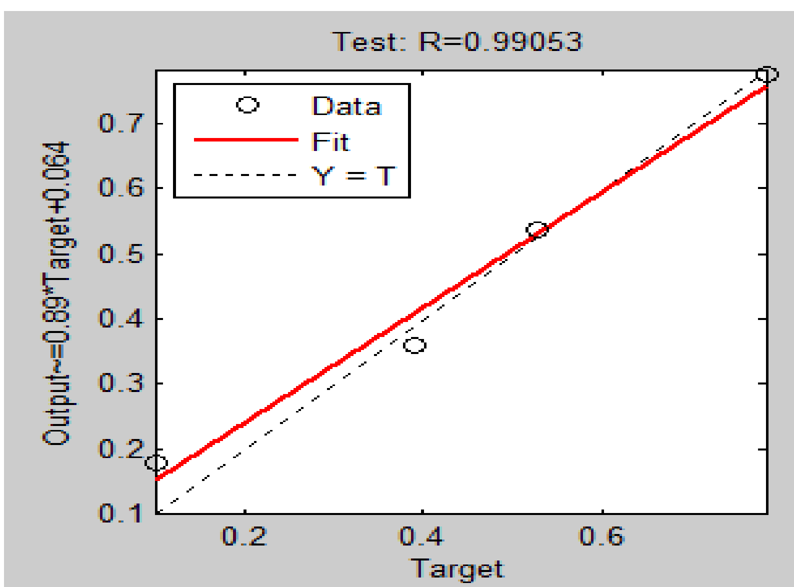

Fig. 4.2. Comparison between the experimental and predicted surface roughness during testing

4.3 Validation of developed ANN model

The figure shows two lines i.e., one dash line and other green line. The dash line shows perfect fit while green line shows linear fit. The best linear fit between the experimental values and predicted values during validation the ANN model is given by the equation as Predicted value =0.97 experimental value +0.007 with 0.971 regression coefficient which indicates excellent correlation between experimental and predicted values of surface roughness.

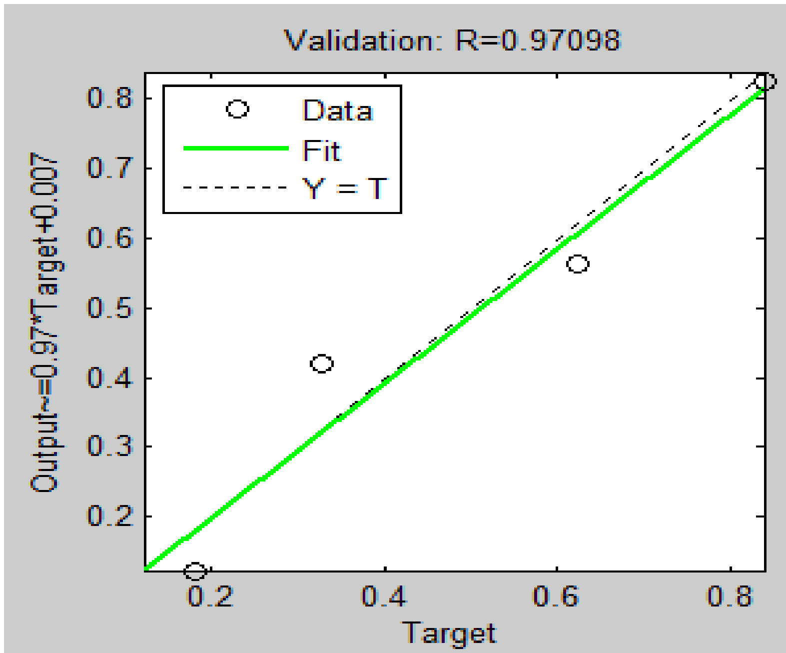

Fig. 4.3. Comparison between the experimental and predicted surface roughness during validation

5. CONCLUSION AND FUTURE SCOPE

This experimental work can be extended further in many more directions. Some ideas or future scope are as follows:

- This experimental work can be performed on many other materials like aluminum alloys, die steel ceramics etc. to find out which is better material to work by comparative study.
- The cutting tool can be changed by many other options like PVD coated tool, CBN tool, diamond tool, ceramic tool according to the work-piece.
- The range of process parameter for experimental work can be change it will surely give the different results.
- The process parameter for experimental work can be change like tool angel, nose radius etc. it will surely give the different results.

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