Study of the Effect of Cutting Conditions on Micro-Hardness in Dry Machining of Hardened Steel En31 with CBN Cutting tool – by ANN Technique

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ABSTRACT

Dry machining is a machining process without coolant and it has become more popular as a finishing process. The purpose of this paper is to obtain a comprehensive understanding of the relation between cutting data and micro hardness during dry turning with CBN cutting tool in En31 hardened steel. The experiments were planned as per L27 orthogonal array with three levels defined for each of the factors in order to develop the knowledge base for Artificial Neural Network (ANN) training and validation. By using ANN sensitivity analysis carried out and how the input parameters speed, feed rate and depth of cut influenced on micro hardness discussed in this present paper.

Keywords: *Dry machining, Micro-hardness, Orthogonal array, Artificial Neural Network.*

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1 INTRODUCTION

Machining hardened steels has become an important manufacturing process, particularly in the automotive and bearing industries. Abrasive processes such as grinding have typically been required to machine hardened steels, but advances in machine tools and cutting materials have allowed hard turning on modern lathes to become a realistic replacement for many grinding applications. There are many advantages of dry machining [1] such as increased flexibility, decreased cycle times, reductions in machine tool costs and elimination of environmentally hazardous cutting fluids.

This paper focuses on dry-machining of the bearing Steel En31 [55-60 HRC] by using CBN cutting tool which is widely used in engineering applications. The chemical composition of the En31 is shown in **Table.1**.

Table 1: Chemical composition of En31 material

Material	C	Mn	Si	Cr	S	P
En31	0.9 – 1.20	0.30-0.75	0.10-0.35	1.0-1.60	0.05	0.05

Zhang Xueping *et al.* [2] reported the effects of process parameters of cutting speed, depth of cut, and feed rate on inducing subsurface compressive residual stresses and then identified the optimal set of process parameters. J.C.Quteiro *et al.* [3] had carried out work on critical issues in machining of difficult - to – cut materials at often associated with short tool life and poor surface integrity where resulting tensile residual stresses on the machined surface significantly affect the component fatigue life. In their study the influence of cutting processes parameters on machining performance and surface integrity generated during dry turning of Inconel 718 and austenitic stainless steel AISI316L with coated and uncoated steel. Outeiro JC *et al.* [4] obesrved in their study, how the processes parameters affect residual stresses in AISI316L and correlated. Y.Matsumoto et al. [5] obesrved in their study that the effect of cutting parameters on residual stresses was investigated in order to find why deep residual stresses are created. Chorng-Jyh Tzeng et al. [6] have optimized turning operations with multiple performance characteristics using Taguchi methods. Azlan Mohd Zain *et al.* [7] have discussed the concept, application, abilities and limitations of ANN technique in the machining process modeling. The future trend of ANN technique has also been discussed. The objective of Artificial Neural Network (ANN) development is to intimate human brain so as to implement the functions such as association, self–organization and generalization. The ANN has advantages of learning ability as well as generalization, thus, can capture non –

linear and complex input – output relationships [8]. The ANN is expected to be capable of solving a complicated problem in a very efficient manner. According to the literature review most of the researcher studied the effect of process parameters on residual stresses but they are not studied on Micro-hardness.

In this present paper, it works to analyze the effects of process parameters i.e. cutting speed (*v*), feed rate (*f*) and depth of cut (*d*) on Micro-hardness through ANN technique during dry turning of hardened steel En31.

2 SELECTION OF PROCESS PARAMETERS

Based on the extensive literature review, process parameters considered for the present study are speed, feed rate and depth of cut, **Table.2** shows the details of the process parameters and their levels considered.

Table 2: Process parameters

Factors	Levels		
Speed, *v* (*m/min*)	91	137	187
Feed rate, *f* (*mm/rev*)	0.076	0.114	0.152
Depth of cut, *d* (*mm*)	0.1	0.15	0.2

3 EXPERIMENTATION

In the present work, a 3^3 factorial design has been chosen; a data sheet has been prepared for the possible combinations. L27 OA was selected [10] for the experimental layout. The details of experimental layout and output response are shown in **Table.3**.

A Hardinge SV150 super precision Lathe was used for all turning operations with CBN as a cutting tool. The tool holder used for all cutting experiments are PSBNR 2525K12. All the work pieces were machined according to the data sheet. After machining Micro-hardness values for all the twenty-seven samples were measured by using Vickers hardness tester at three points on the each work piece and take the average value, noted in the **Table.3**.

4 RESULTS AND ANALYSIS

By using statistical tool to develop interaction plots for Micro-hardness with CBN tool as shown in **Fig.1**. If the lines in the interaction plots are

Table 3: Experimental layout and output response

Sl. no	Cutting Speed, *v* (*m/min*)	Feed Rate, *f* (*mm/rev*)	Depth of cut, *d* (*mm*)	Micro hardness (HV100)
1	91	0.076	0.1	1035.5
2	91	0.114	0.1	975.5
3	91	0.152	0.1	922
4	91	0.076	0.15	960.75
5	91	0.114	0.15	949.25
6	91	0.152	0.15	896.25
7	91	0.076	0.2	869
8	91	0.114	0.2	954.25
9	91	0.152	0.2	951.75
10	137	0.076	0.1	1057.25
11	137	0.114	0.1	1093
12	137	0.152	0.1	1001
13	137	0.076	0.15	934.25
14	137	0.114	0.15	979.25
15	137	0.152	0.15	949.75
16	137	0.076	0.2	1018.25
17	137	0.114	0.2	947.75
18	137	0.152	0.2	989.5
19	183	0.076	0.1	849.25
20	183	0.114	0.1	765.5
21	183	0.152	0.1	780.5
22	183	0.076	0.15	896.75
23	183	0.114	0.15	825.75
24	183	0.152	0.15	823.25
25	183	0.076	0.2	807
26	183	0.114	0.2	821.75
27	183	0.152	0.2	921.5

parallel then there are no interaction between the parameters, this implies that the change in the mean response from low level to high level of a factor does not depend on the level of the other factor. If the lines are not parallel interaction exists between the parameters and greater the degree of departure from being parallel, the stronger the interaction

From the **Fig.1**, it may be concluded that when the speed increases, the feed rate increases there by the interaction effect revels that there exist considerable

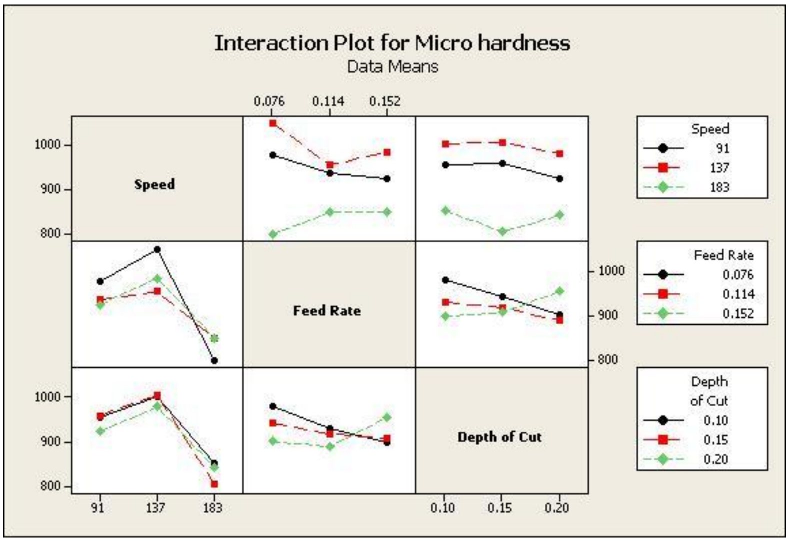

Figure 1: Interaction plots for micro hardness with CBN tool.

significance. When feed rate increases, the depth of cut also increases there by the interaction effect reveals that there exists no significance. When speed increases, the depth of cut also increase there by the interaction effect reveals that there exits less significance.

The **Fig.2**, **Fig.3** and **Fig.4** Shows Micro-hardness versus depth of cut at fixed speed and feeds. From the above graphs it may concluded that at particular speed and different feeds, the depth of cut increases the Micro-hardness value increase or decrease.

From the above analysis, it is very difficult to predict the effect of process parameters on Micro-hardness. Hence it is proposed to develop ANN.

5 ANN APPROACH

There are three input parameters (Speed, feed rate and depth of cut) and 27 output parameter Micro-hardness. Some of the most common ANN architectures considered to develop the model by using neural solutions software [9] are: Multilayer Perceptron (MLP), Generalized Feed forward, Modular, Jordan/Elman, Principal Component Analysis (PCA), Radial Basis Function (RBF), General Regression Neural Network (GRNN), Probabilistic Neural Network (PNN), Self-Organizing Feature Map (SOFM), Time-Lag Recurrent Network (TLRN), Recurrent Network, and Support Vector Machine (SVM).

Architecture is selected based on the lowest Mean Square Error [MSE) value. Once the network architecture is selected, parameters such as the number of

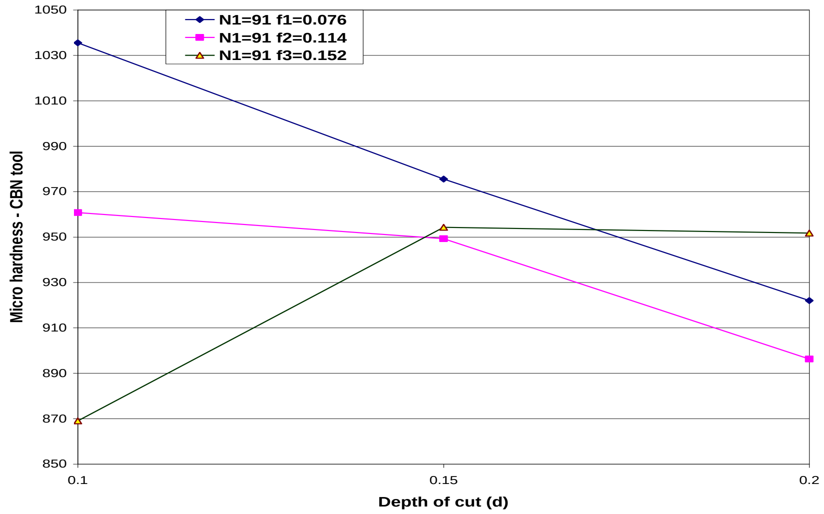

Figure 2: Micro-hardness versus depth of cut (d) at $N_1 = 91$, $f_1 = 0.076$, $f_2 = 0.114$, $f_3 = 0.152$-CBN tool.

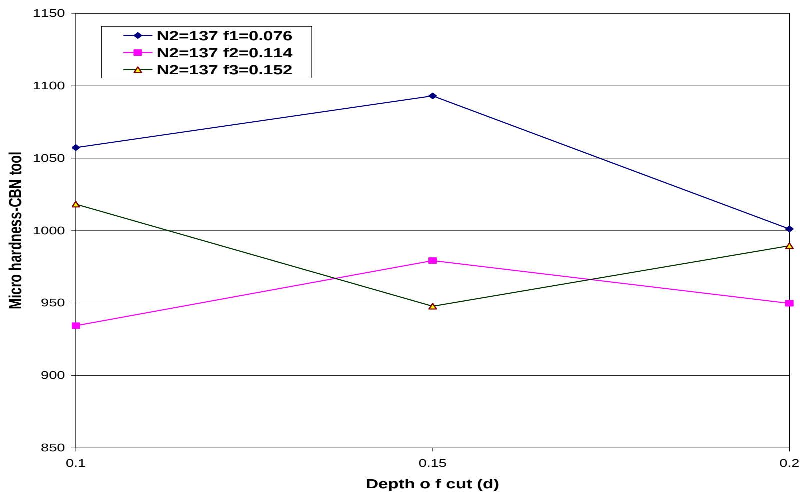

Figure 3: Micro-hardness versus depth of cut (d) at $N_1 = 137$, $f_1 = 0.076$, $f_2 = 0.114$, $f_3 = 0.152$-CBN tool.

hidden layers, the number of epochs and the learning algorithm can be customized. Among all the above NN models studied, principle component analysis networks (PCA) gives least MSE of 0.000747041 CBN used as cutting tool with 29000 epochs after many trail and error combinations. Details of PCA Neuro-fuzzy model data sets are given in **Table.4**.

Table 4: Model data sets

Training data sets	Cross validation data sets	Testing data sets	Production data sets
21	2	2	2

ANN training was carried out and the variation of MSE during the training as shown in **Fig.5**. In the present study the desired MSE achieved after 28000. Experimental values and ANN predicted values along with percentage error are presented in the below **Table.5**. It is clear that the model has predicted the Micro-hardness values with least percentage error less than zero.

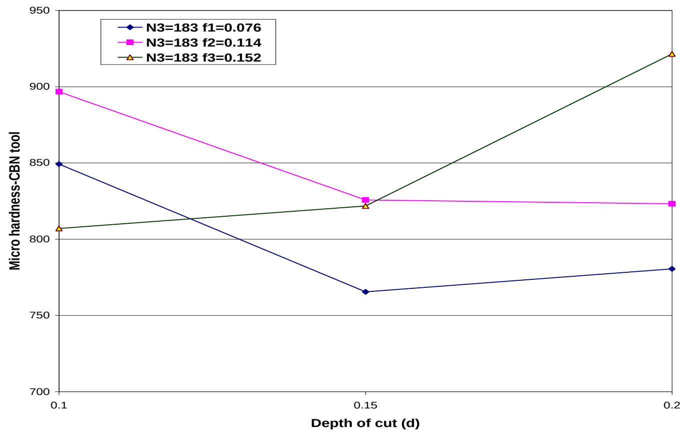

Figure 4: Micro hardness versus depth of cut [d] at N_1=137, f_1=0.076, f_2=0.114, f_3=0.152-CBN tool.

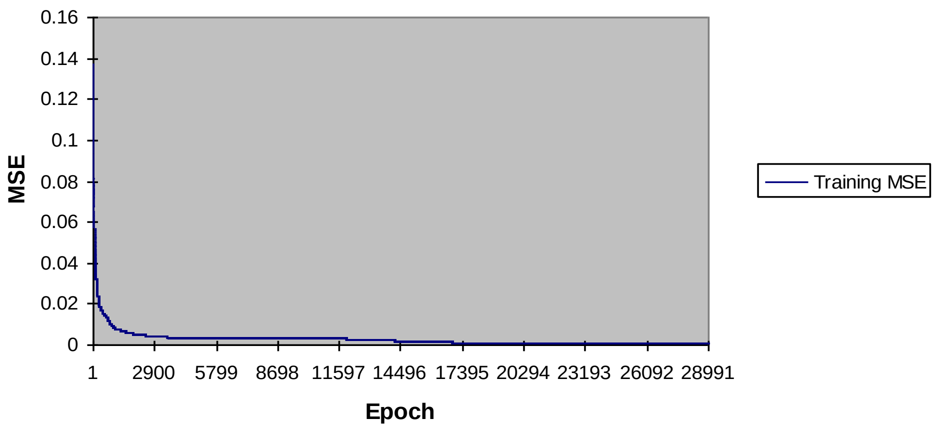

Figure 5: The variation of Mean Squared [MSE] with number of Epochs.

Table 5: % error of predicted values of production data

Cutting Speed, *v* (*m/min*)	Feed rate, *f* (*mm/rev*)	Depth of cut, *d* (*mm*)	Micro hardness [HV100]	ANN predicted	% error
137	0.076	0.2	1018.25	1017.613	0.06261
137	0.152	0.1	1001	1000.563	0.04371
91	0.152	0.2	951.75	950.8614	0.09345
137	0.114	0.2	947.75	948.1428	0.041428
91	0.114	0.1	975.5	975.7081	0.021333
137	0.076	0.1	1057.25	1057.224	0.00247
137	0.114	0.1	1093	1093.067	0.00613
183	0.114	0.1	765.5	766.284	0.102313
183	0.114	0.15	825.75	826.1044	0.042904
91	0.076	0.2	869	882.7354	1.556004
91	0.152	0.1	922	941.4179	2.062618
137	0.152	0.15	949.75	950.6929	0.099178
183	0.076	0.15	896.75	896.56	0.0212
137	0.076	0.15	934.25	934.2654	0.001652
137	0.114	0.15	979.25	980.8174	0.159805
183	0.076	0.2	807	806.5091	0.06086
91	0.152	0.15	896.25	883.347	1.46069
183	0.114	0.2	821.75	821.9027	0.018576
91	0.114	0.15	949.25	948.0092	0.13089
183	0.152	0.2	921.5	921.2703	0.02493
137	0.152	0.2	989.5	989.2968	0.02054
91	0.076	0.15	960.75	940.8064	2.11984
183	0.152	0.15	823.25	823.3569	0.012989
91	0.114	0.2	954.25	892.4737	2.66562
91	0.076	0.1	1035.5	1093.913	2.12906
183	0.076	0.1	849.25	758.2033	1.043262
183	0.152	0.1	780.5	1055.094	2.448975

From **Fig.6**, it was found that the predicted and experimental values were very fairly close to each, which means the model developed is justified.

Sensitivity analysis is carried out and presented in **Fig.7**. From the graph, it is clear that Micro-hardness is highly influenced by the input parameter Speed whose sensitivity value is 70.11. Micro hardness is almost equally influenced by the input parameter feed and depth of cut whose sensitivity values are 38.49, 37.39.

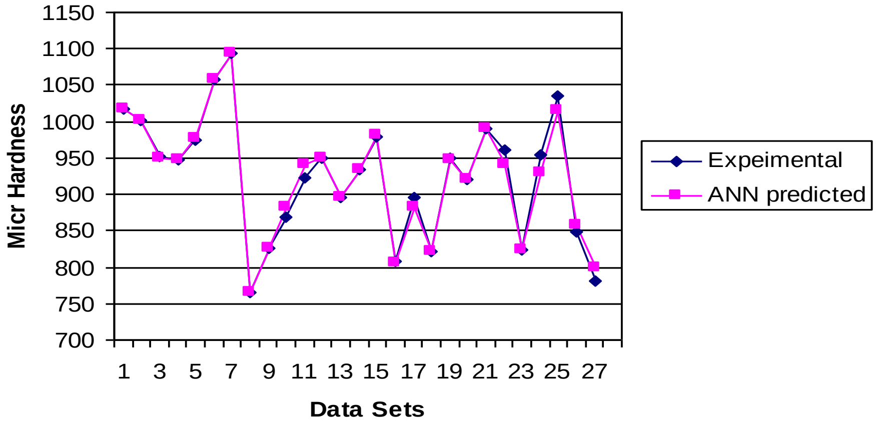

Figure 6: Experimental and network predicted values of Micro-hardness.

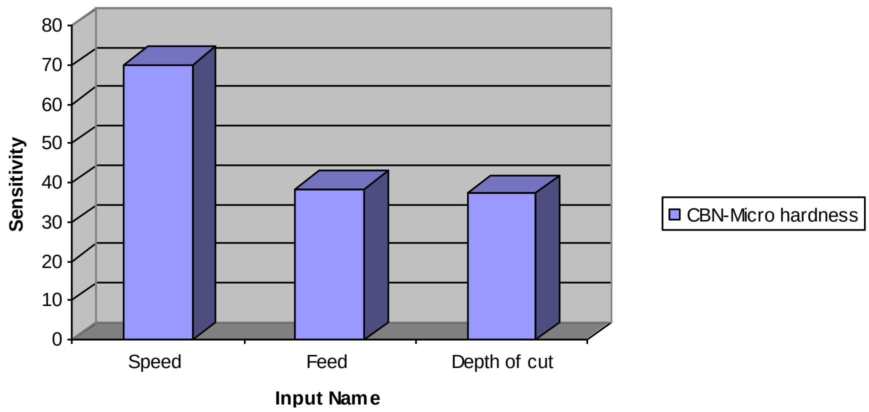

Figure 7: Sensitivity of residual stresses -CBN cutting tool with speed, feed and depth of cut.

6 CONCLUSIONS

ANN approach provides a systematic and effective methodology for the optimization.

The following conclusions are drawn from the present works:

(i) The ANN model has predicted the Micro-hardness values with least percentage error less than zero.

(ii) It was found that the predicted and experimental values were very fairly close to each, which means the model developed is justified.

(iii) From the sensitivity analysis it was that the input parameter speed highly influenced on Micro-hardness.

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