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Experimental analysis of cutting tool forces based on flank wear at optimum cutting conditions in hard turning of AISI H13

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Abstract- In this experimental study, the AISI H13 tool steel (58 HRC) is used for the experiment with CBN tool in a hard turning operation. The tests are carried out at various cutting speeds, feed rates and depth of cut as input parameter. During the experiment, cutting forces, flank wear and surface-roughness values are determined as output parameters. Three components (Ff, Ft and Fc) of the Cutting forces are measured during the tests using a lathe tool dynamometer, while the machined surface-roughness values are determined using a surface roughness tester. The tool maker's microscope is used to measure the flank wear. The measured values of cutting forces, surface-roughness and flank wear are used for the modeling with an artificial neural network approach. Artificial Neural Network (ANN) model is developed for the cutting forces, and surface roughness. Predicted values obtained from the ANN model are compared with experimental value. The results obtained indicate that the proposed modeling approach could be effectively used to predict the three component cutting force system and surface-roughness during hard turning. ANN model provides a possible way to a reduce time and save the cost of experiments.

Keywords: *Hard turning, CBN tool, Cutting forces, Surface roughness, Flank wear, artificial neural network*

I. INTRODUCTION

Hard turning is performed on hardened steels in the 45 to 68 Rockwell hardness range using a variety of tool materials preferably CBN [2]. Hard turning has been applied in many areas like production of bearings, gears, shafts, axles, and other mechanical components. Turning of these types of materials require hard and tough cutting tools like CBN and PCBN tools. These types of cutting tools will reduce flank wear and withstand the heat generation. Tool wears are complex phenomenon. Tool wear is common in all the machining processes and depend on the hardness of the work materials, type of tool, rigidity of the machine, heat, formation of chips and cutting parameters [1]. All these factors also contribute to the values of the cutting forces. Cutting forces, tool wear, surface roughness and temperature induced by the cutting process and work material are the major causes of error in hard turning. CBN and PCBN tools possess excellent mechanical properties such as high temperature strength, ability to maintain its shape at high temperature and hardness second to diamond [1]. Although grinding is known to produce good surface finish at relatively high feed rates, hard turning can produce as good or better surface finish at significantly higher material removal rates without using coolant or special tooling[2]. This process has been developed as an alternative to the grinding process in a bid to reduce the number of setup changes, product cost and lead time without compromising on surface quality to maintain competitiveness [4, 5].

Artificial neural network (ANN) approach is an accurate and powerful tool for machining process modeling, as it permits to save much time and money generally spent in experimental procedures. A large amount of works have been carried out on forces modeling which have shown that ANN approach is more accurate and faster than many other analytical and numerical cutting force modeling methods[6].

1.1 Literature review

S.Thamizhmanii et al. [1] conducted study on a flank wear on CBN and PCBN tools due to cutting forces and develop the clear relation between them. After the the experiments concluded that lower the cutting force leads to low flank wear and low cutting force provides good dimensional accuracy of the work material including the surface roughness.

Gaurav Bartarya et al. [2] investigated effect of cutting parameters on cutting force and surface roughness during finish hard turning AISI52100 grade steel. After the experiment depth of cut was found to be the most influential parameter affecting the three cutting forces followed by the feed. Cutting speed was least significant in case of axial and radial force models but was not significant for the regression model of cutting force [3]. The most energy efficient cut can be achieved for relatively lower and moderate cutting speeds with moderate depth of cut in the range of parameters selected for nearly all feed values selected in the range.

D.I. Lalwani et al. [3] also reported that Effect of cutting parameters on cutting forces and surface roughness. After the experiment findings are Cutting speed has no significant effect on cutting forces and surface roughness. In Feed force model, the depth of cut is most significant factor with 89.05% contribution in the total variability of model whereas feed rate has a secondary contribution of 6.61% in the model. In Thrust force model, the feed rate and depth of cut are significant factor with 46.71% and 49.59% contribution in the total variability of model, respectively. In Cutting force model, the feed rate and depth of cut are the most significant factors affecting cutting force and account for 52.60% and 41.64% contribution in the total variability of model, respectively.

S. Thamizhmnaii et al. [4] conducted study on Tool flank wear. The conclusions after experiments were drawn that the higher flank wear occurred at low cutting speed with high feed rate and more depth of cut. i.e. at cutting speed of 125 m/min, feed rate of 0.125 mm/rev and DOC of 1.00 mm. The influence of tool flank wea r was due to abrasive action between tool tip and cutting tool, hard carbides in the work piece material. The flank wear was also due to heat generated at low cutting speed [1].

M. Ibrahim et al. [5] carried out work on Wear development and cutting forces on CBN cutting tool during Hard turning of different hardened steels. According to the results of this experimentation, the conclusions can be obtained is that there is a clear relationship between the chemical composition, micro structure and machinability of hardened steel [4]. A combination of metallic binder and high CBN content results in rapid wear development in continuous turning of hardened steel.

Souad Makhfi et al. [6] reported that a large number of interrelated machining parameters have a great influence on cutting forces. And concluded that neither using double hidden layer has shown advantage over single hidden layer. A sigmoid activation function has been chosen in hidden layer and a linear one in output layer. Levenberg–Marquardt (LM) algorithm has been compared to Levenberg–Marquardt using Bayesian Regularization (BR/LM). It has appeared that using Bayesian Regularization permits to avoid overfitting in training, which gives thus a major advantage over simple LM algorithm. And finally, a various number of neurons in hidden layer have been tested, from 1 to 35. It has been noticed first that the algorithm converges when this number reaches 11, and second that a minor overfitting appears when the number of neurons exceeded 13.

Murat Tolga Ozkan et al. [7] studied the influences of the machining parameters (cutting speed, feed rate, depth of cut and cutting-tool material) on the cutting forces and surface roughness.In conclusion, a surface-roughness prediction not requiring an experimental study with ANN models can provide both simplicity and fast calculation. It is shown that an ANN model can be used as an effective and alternative method of experimental studies improving both the time and economical optimization of the machining.

Djordje Cica et al. [8] working on an Artificial Intelligence Approach for modeling of the Cutting Forces in Turning Process Using Various Methods of Cooling and Lubricating. In this study, two different methodologies, namely, ANN and ANFIS based modeling as a potential modeling technique for developing optimal cutting force prediction model are compared and discussed. which indicates that both models can be used effectively to predict the forces in turning operations.

Nikolaos M. Vaxevanidis et.al. [9] concluded that the best performance was obtained from the ANN with FFBP architecture, one hidden layer and seven neurons on the hidden layer. The results obtained indicate that the proposed modeling approach could be effectively used to predict the three component cutting force system during turning of AISI D6 tool steel, thus supporting decision making during process planning and providing a possible way to reduce time and to reduce cost of experiments.

Konanki M. Naidu et.al [10] used two different types of modeling techniques i.e. multiple linear regression and Artificial Neural Network were used in his present study. After experiments and analysis, concluded that from the multiple linear regression analysis the interaction terms of speed, feed and depth of cut are not significant on the response surface roughness. The average absolute percentage error in predicting the surface roughness values by ANN model is 2.24.

II. MATERIAL AND EXPERIMENTAL PROCEDURE

The experimental procedure was designed using full factorial method **(Table 2)**. A three parameters was selected with each parameter having three levels **(Table 1)**.The three turning parameters (factors) considered in this study are: cutting speed (V, m/min), feed rate (F, mm/rev) and depth of cut (D, mm). A 3D cutting force system was considered according to standard theory of oblique cutting [9]. Columns 1, 2, and 3 of Table 2 are assigned to cutting speed (m/min), feed rate (mm/rev), and depth of cut (mm), while the rest columns left vacant.

Table 1. Factors and Their range

Factors	1	2	3
Speed (m/min)	82	119	156
Feed (mm/rev)	0.05	0.06	0.07
Depth of cut (mm)	0.2	0.3	0.4

Turning experiments were conducted using a HMT NH22 conventional lathe. A SANDVIK CBN tool insert, coded as CNGA120408S01030A, was used during the present series of experiments. The tool has Diamond shape (included angle 80°) and Nose radius was 0.8mm.

Table 2. Experimental result

Test No.	**Speed (m/min)**	**Feed (mm/rev)**	**Depth of cut (mm)**	**Ff (N)**	**Ft(N)**	**Fc(N)**	**Surface roughness (μm)**
1	82	0.05	0.2	130	150	290	2.543
2	119	0.05	0.2	140	180	320	1.232
3	156	0.05	0.2	100	130	170	0.425
4	82	0.06	0.2	130	210	390	1.112
5	119	0.06	0.2	120	200	250	1.507
6	156	0.06	0.2	220	250	250	1.231
7	82	0.07	0.2	240	280	300	0.622
8	119	0.07	0.2	220	260	280	0.480
9	156	0.07	0.2	210	250	280	0.504
10	82	0.05	0.3	160	200	240	3.892
11	119	0.05	0.3	200	210	260	4.250
12	156	0.05	0.3	210	210	260	2.946
13	82	0.06	0.3	270	220	330	0.896
14	119	0.06	0.3	240	230	320	0.620
15	156	0.06	0.3	90	130	120	0.560
16	82	0.07	0.3	100	130	130	0.517
17	119	0.07	0.3	90	110	120	0.538
18	156	0.07	0.3	60	100	110	0.558
19	82	0.05	0.4	60	80	90	0.672
20	119	0.05	0.4	50	80	90	0.648
21	156	0.05	0.4	50	70	80	0.523
22	82	0.06	0.4	50	60	80	0.502
23	119	0.06	0.4	50	60	90	0.530
24	156	0.06	0.4	40	50	80	0.504
25	82	0.07	0.4	40	50	70	0.486
26	119	0.07	0.4	40	60	70	0.541
27	156	0.07	0.4	40	60	70	0.570

Note that the accurate determination of cutting forces is essential for processes performance, for the evaluation of machining accuracy as well as for tool wear studies and for developing machinability criteria [9].
The test material was a tool steel AISI H 13 and their chemical composition is shown in **Table 3**, with hardness 58 HRC. The test specimens were in the form of bars; 90 mm in diameter and 380 mm in length.

Table 3. Chemical Composition of work piece material

C	Si	Mn	Ph	Su	Cr	Mo	Va
0.382	0.940	0.340	0.029	0.022	4.870	1.260	1.040

Cutting force components were measured using a three-channel EEE-lathe tool dynamometer. The output from the dynamometer is amplified through a amplifier. The three components of cutting forces namely the feed force (Fz), the radial thrust force (Fx) and the tangential cutting force (Fy) were monitored. The obtained results for the responses (Fz, Fx, Fy) are presented in **Table 2**. Mitutoyo SJ-210 surface roughness tester was used to measure the surface roughness. To measure the flank wear tool maker's microscope used.

Flank wear of CBN tool was measured at every 1 cut (at every 65 mm cutting length) by using tool maker's microscope in table 4. Flank wear at optimum condition set no.3 (156 m/min cutting speed, 0.05 mm/rev feed rate, 0.8 mm nose radius and 0.2 mm doc).Result of this work is shown in **Table 4.**

Table 4. Tool flank wear of CBN cutting tool insert

Sr. No.	Cutting Length (mm)	Tool force (N)			Surface roughness (μm)	Avg. Flank wear (mm)
		Ff	Ft	Fc		
1	65	90	120	150	0.431	0.094
2	130	90	130	150	0.496	0.15
3	195	10	110	160	0.580	0.18
4	260	110	140	170	0.735	0.204
5	325	130	150	170	0.856	0.240
6	390	120	150	190	0.920	0.295
7	455	120	160	200	1.347	0.310
8	520	140	180	230	1.690	0.39

III RESULT AND DESCUSION

3.1 ANN modeling:

The ANNs are best tools in modeling the manufacturing processes. These techniques have proved better predicted accuracy than the conventional modeling techniques. The following paragraphs describe the working principle of the ANN structure. In a multilayer feed-forward network, the processing elements are arranged in layers and only the elements in the adjacent layer are connected. The strength of connection between the two neurons of adjacent layers is expressed by the weight. In the feed-forward network, the weighted connections feed activations only in the forward direction from the input to output layer. Figure 1 shows the structure of a fully connected feed-forward ANN with Three layers, one input, one hidden and one output layers of the network [10].

Literature reviews show ANN models have better prediction capability than the regression model, in these research work developed an ANN model to predict feed force. This subsection describes pre processes, model design and training, model simulation and post processes in the generation of ANN prediction models.

Before applying inputs and outputs for ANN training, data have to be converted into a range of 0 to 1 or -1 to 1 i.e. Data should be normalized for ANN training. An equation (1) was used for data normalization which ranges the data to [0, 1]. The normalized result table is shown in **table 5**.

$$x_n = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

Where,

x_n = Normalized Value of Variable x

x = Value of Variable x

x_{min} = Minimum Value of variable x

x_{max} = Maximum Value of Variable x

Graphical user interface (GUI) uses in the neural network toolbox in MATLAB. All 27 experiments run set the train in neural network, different network configuration with different number of hidden neurons was trained and their performance is checked. Neurons number in hidden layer varies until we get the best prediction model.

Table 5. Normalized Experiment Result Table

Input parameters			Output parameters			
Cutting speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Feed force (N)	Thrust force (N)	Cutting force (N)	Ra (µm)
0	0	0	0.391304	0.434783	0.6875	0.553725
0.5	0	0	0.434783	0.565217	0.78125	0.21098
1	0	0	0.26087	0.347826	0.3125	0
0	0.5	0	0.391304	0.695652	1	0.179608
0.5	0.5	0	0.347826	0.652174	0.5625	0.282876
1	0.5	0	0.782609	0.869565	0.5625	0.210719
0	1	0	0.869565	1	0.71875	0.051503
0.5	1	0	0.782609	0.913043	0.65625	0.014379
1	1	0	0.73913	0.869565	0.65625	0.020654
0	0	0.5	0.521739	0.652174	0.53125	0.906405
0.5	0	0.5	0.695652	0.695652	0.59375	1
1	0	0.5	0.73913	0.695652	0.59375	0.659085
0	0.5	0.5	1	0.73913	0.8125	0.123137
0.5	0.5	0.5	0.869565	0.782609	0.78125	0.05098
1	0.5	0.5	0.217391	0.347826	0.15625	0.035294
0	1	0.5	0.26087	0.347826	0.1875	0.024052
0.5	1	0.5	0.217391	0.26087	0.15625	0.029542
1	1	0.5	0.086957	0.217391	0.125	0.034771
0	0	1	0.086957	0.130435	0.0625	0.064575
0.5	0	1	0.043478	0.130435	0.0625	0.058301
1	0	1	0.043478	0.086957	0.03125	0.025621
0	0.5	1	0.043478	0.043478	0.03125	0.020131
0.5	0.5	1	0.043478	0.043478	0.0625	0.027451
1	0.5	1	0	0	0.03125	0.020654
0	1	1	0	0	0	0.015948
0.5	1	1	0	0.043478	0	0.030327
1	1	1	0	0.043478	0	0.037908

Training process performs in the MATLAB software in which nftool is essential to train the data. In this process inputs and output is fixed and vary the neuron number in hidden layer until predicted output value comes close to experimental target value. Train the network by adjusting the number of neurons in hidden layer which reduce the error. How many times we train the network it predict the different output. To stop the training criteria should be decided before the train network. It may depend upon the goal or epoch or any other training stop criteria.

3.2 Checking accuracy of ANN model

Accuracy of ANN model prediction is depending upon the Root mean square error (RMSE), the Coefficient of multiple determination (R^2) values has been used for making comparisons.
Each processing elements first performs a weighted accumulation of the respective input values and then passes the result through an activation function. Except for the input layer nodes where no computation is done, the net input to each node is the sum of the weighted output of the nodes in the previous layer [10].

Table 6.Dataset used for ANN analysis for Ff and Ft

Experimental Feed force (N) aj	ANN predicted Feed force (N) pj	Error (N) aj - pj	Experimental Thrust force (N) aj	ANN predicted Thrust force (N) pj	Error (N) aj - pj
130	129.9799	0.020106997	150	150.0002	0.000199
140	140.1707	0.170689689	180	180.0436	0.043577
100	99.81975	0.180248512	130	130.2254	0.225382
130	130.0163	0.016303969	210	209.1708	0.829193

120	119.7609	0.239053431	200	199.9138	0.086212
220	220.3021	0.302088955	250	249.5575	0.442493
240	238.3761	1.623935045	280	280.6327	0.632696
220	222.8258	2.825838147	260	260.0376	0.03763
210	208.6565	1.343453066	250	250.2478	0.247771
160	159.7805	0.219472134	200	200.0253	0.025339
200	200.6758	0.675764841	210	210.6784	0.678395
210	209.517	0.482986193	210	209.9756	0.02435
270	270.1242	0.124209216	220	219.7372	0.262765
240	239.6421	0.357877393	230	229.5571	0.442919
90	90.23245	0.232453842	130	129.9901	0.009932
100	100.2495	0.249513633	130	130.2318	0.231759
90	89.58649	0.413506626	110	109.9406	0.059365
60	60.17135	0.171345969	100	100.0577	0.057693
60	60.00659	0.006591613	80	80.02918	0.029183
50	50.10876	0.108761253	80	80.56534	0.565341
50	49.87622	0.123784811	70	69.98963	0.010373
50	49.66733	0.332665996	60	59.21947	0.780532
50	50.18558	0.185579631	60	57.35796	2.642035
40	40.09857	0.09857298	50	50.06574	0.065737
40	40.20894	0.208937554	50	51.54516	1.545155
40	39.76632	0.233676655	60	61.30622	1.306218
40	39.97943	0.020565395	60	59.94238	0.057623
RMSE	0.003144		RMSE	0.003154	
R^2	0.9999		R^2	0.9999	

Table 7. Dataset used for ANN analysis for Fc and Ra

Experimental Cutting force (N) aj	ANN predicted Cutting force (N) pj	Error (N) aj - pj	Experimental surface roughness (µm) aj	ANN predicted surface roughness(µm)pj	Error (µm) aj - pj
290	291.4391	1.439084	2.543	2.542848	0.000152
320	319.8307	0.169277	1.232	1.239732	0.007732
170	170.3891	0.38905	0.425	0.42674	0.00174
390	389.1632	0.836783	1.112	1.113256	0.001256
250	249.897	0.103046	1.507	1.497015	0.009985
250	249.89	0.11003	1.231	1.232342	0.001342
300	300.8725	0.872453	0.622	0.620834	0.001166
280	281.0907	1.090746	0.48	0.484054	0.004054
280	279.7682	0.231773	0.504	0.501173	0.002827
240	241.0184	1.018417	3.892	3.890429	0.001571
260	257.6993	2.300696	4.25	4.25227	0.00227
260	260.6231	0.623062	2.946	2.946003	3.10E-06
330	328.8729	1.127119	0.896	0.898436	0.002436
320	321.7133	1.713327	0.62	0.613054	0.006946
120	119.4617	0.538306	0.56	0.561866	0.001866
130	131.0367	1.036737	0.517	0.516039	0.000961
120	118.345	1.655005	0.538	0.543427	0.005427
110	109.5225	0.477496	0.558	0.559976	0.001976

90	89.37723	0.622768	0.672	0.672552	0.000552
90	90.7776	0.777601	0.648	0.618668	0.029332
80	80.20169	0.201692	0.523	0.538394	0.015394
80	80.00551	0.005509	0.502	0.499146	0.002854
90	91.10013	1.100132	0.53	0.55988	0.02988
80	79.61416	0.385836	0.504	0.52459	0.02059
70	70.64611	0.646112	0.486	0.487738	0.001738
70	69.27631	0.723691	0.541	0.533749	0.007251
70	69.51148	0.488524	0.57	0.538015	0.031985
RMSE	0.002934		RMSE	0.003098	
R^2	0.9999		R^2	0.9999	

3.3 Prediction of feed force (Ff):

Linear Regression Fitting of ANN Model:
Performance on the training can be measured by the training value R, this regression plot is created by the MATLAB software. This regression plot shows the variation in Target value and predicted value by ANN. As the predicted value near to target value the error will be reduced. As the training value R move toward the 1 the errors also reduce. In this regression plot all 27 data lie on fit line and the value of R is 0.9999 which indicated the ANN predicated output values are near to target values. Target values are experimental values.

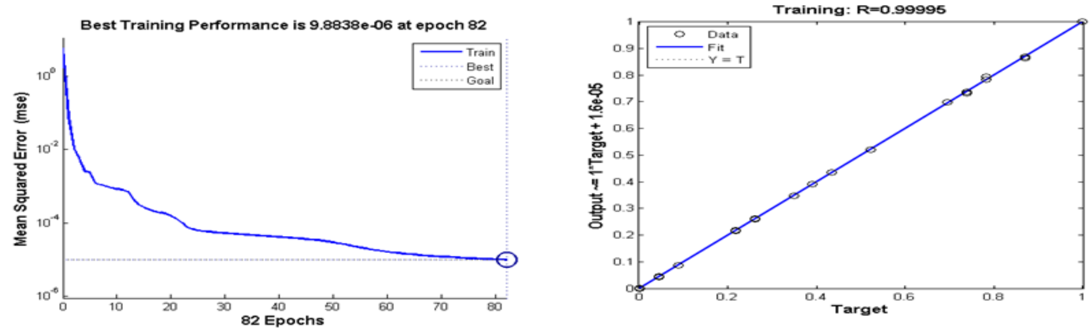

Figure 1 Training Performance Graph and Regression plot for feed force

Figure 1 shows the comparison between the experimental output (Target value) and ANN model predicted output Value. In this graph ANN predicted output value of feed force is close to the Experimental result of feed force. Minimum feed force predicted by ANN model is 39.766 N at cutting speed 119m/min, feed 0.07 mm/rev and 0.4 mm depth of cut.

3.4 Prediction of thrust forces (Ft)

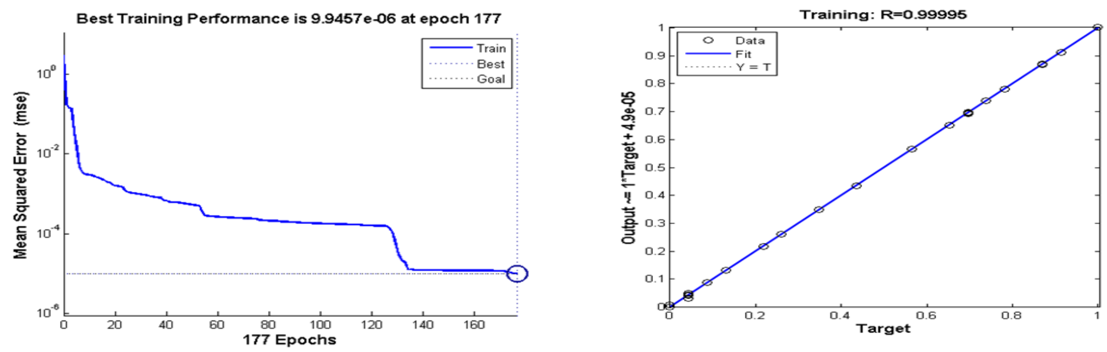

Figure 2. Training Performance Graph and Regression plot for thrust force

Figure 2 shows the comparison between the experimental output (Target value) and ANN model predicted output Value. In this graph ANN predicted output value of thrust force is close to the Experimental result of thrust force. Minimum predicted thrust force found 50.06 N at cutting speed 156m/min, feed 0.06 mm/rev and 0.4 mm depth of cut.

3.5 Prediction of cutting force (Fc)

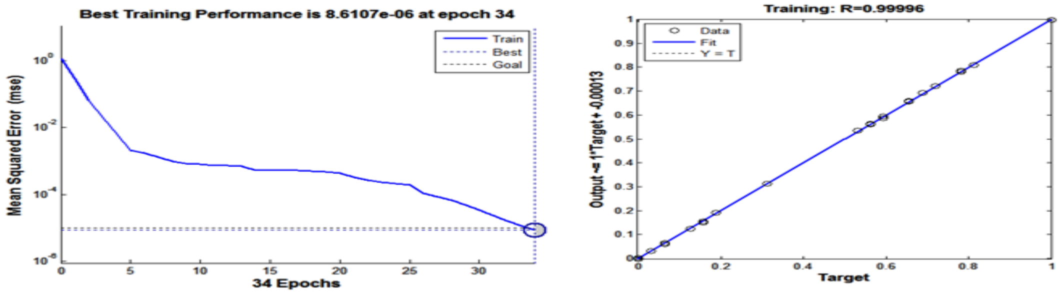

Figure 3. Training Performance Graph and Regression plot for cutting force

Figure 3 shows the comparison between the experimental output (Target value) and ANN model predicted output Value. In this graph ANN predicted output value of cutting force is close to the Experimental result of cutting force. Minimum predicted cutting force observed 69.276 N at cutting speed 119 m/min, feed 0.07 mm/rev and 0.4 mm depth of cut.

3.6 Prediction of Surface roughness (Ra)

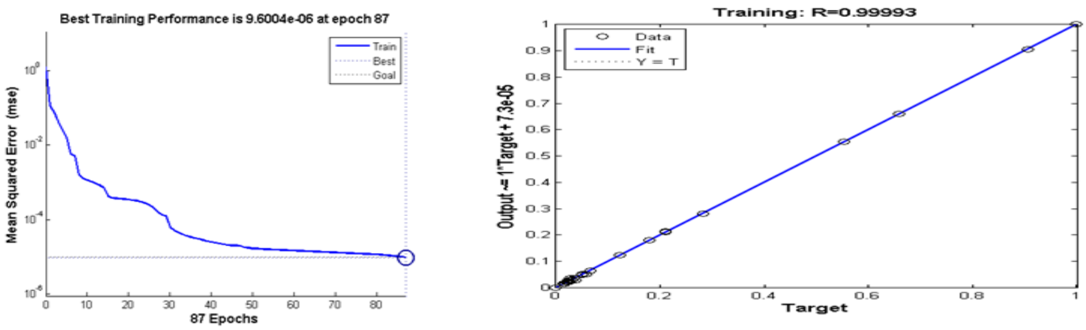

Figure 4. Training Performance Graph and Regression plot for surface roughness

Figure 4 shows the comparison between the experimental output (Target value) and ANN model predicted output Value. In this graph ANN predicted output value of Ra is close to the Experimental result of Ra. Minimum predicted surface roughness is 0.42µm at cutting speed 156 m/min, feed 0.05 mm/rev and 0.2 mm depth of cut.

3.7 Flank wear

During the experiment, it is noted that value of the average flank wear and cutting forces increases with respect to each other and also increases with respect to length of work piece but value of the surface roughness increases which is not desirable.

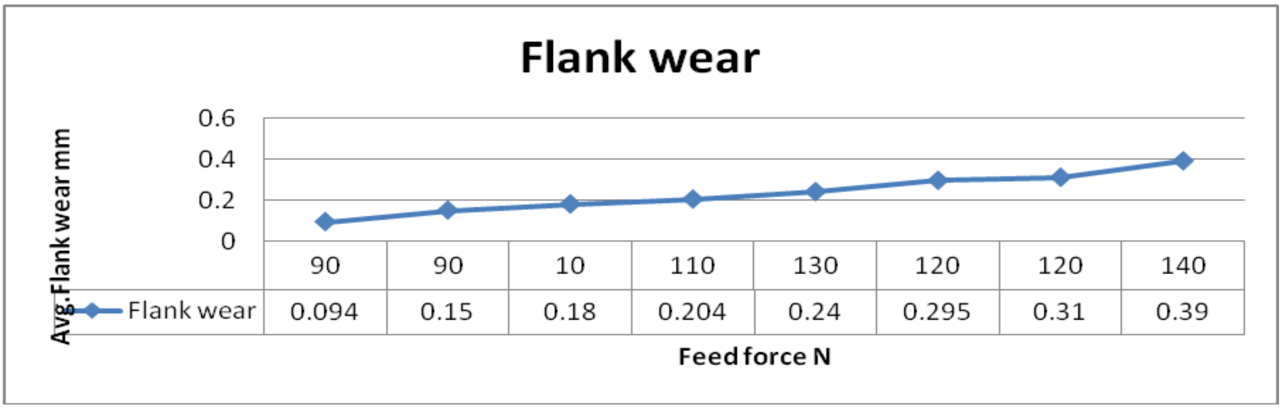

Figure 5 .Effect of feed force on flank wear

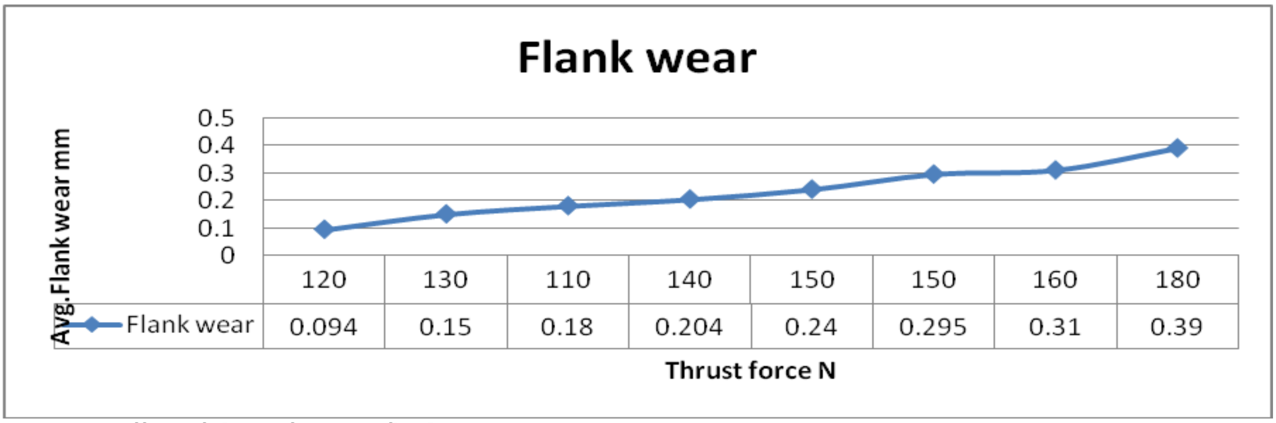

Figure 6 .Effect of thrust force on flank wear

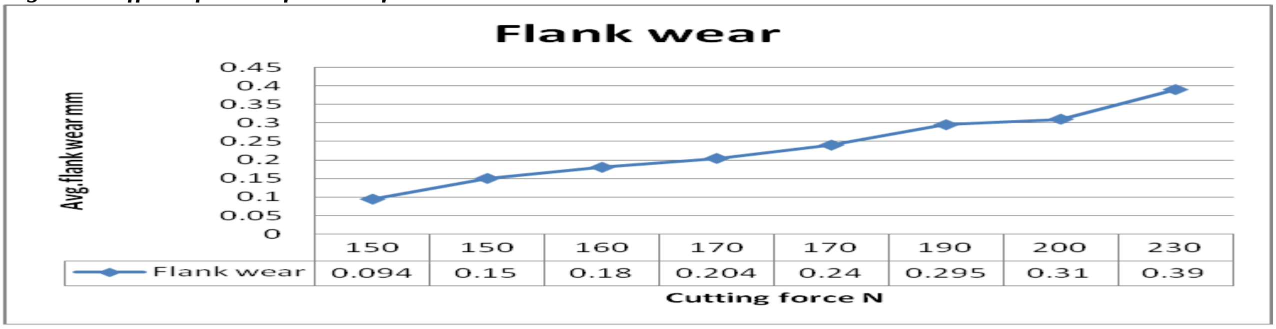

Figure 7 .Effect of cutting force on flank wear

IV. CONCLUSION

In the present study, ANN model has been developed for predicting the three components of cutting tool forces and surface roughness during hard turning of AISI H13.The result of the present work are summarized as follow.

The average absolute percentage error in predicting the feed force, thrust force, cutting force and surface roughness values by ANN model is 0.36, 0.51, 0.50 and 1.16 respectively. Predicted values of cutting tool forces and surface roughness is very close to experimental value. Minimum predicted feed force is 39.76 N at cutting speed 119m/min, feed 0.07 mm/rev and 0.4 mm depth of cut. Minimum predicted thrust force found 50.06 N at cutting speed 156m/min, feed 0.06 mm/rev and 0.4 mm depth of cut. Minimum predicted cutting force observed 69.276 N at cutting speed 119 m/min, feed 0.07 mm/rev and 0.4 mm depth of cut. Minimum predicted surface roughness is 0.42µm at cutting speed 156 m/min, feed 0.05 mm/rev and 0.2 mm depth of cut. Average flank wear increases with increase in cutting tool forces and cutting length. Surface roughness becomes poor with increase in flank wear.

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