PREDICTION OF SURFACE ROUGHNESS BY MEASURING FLANK WEAR AND CUTTING FORCES IN TURNING PROCESS

Deepak Lawrence K.*, Lakshmanan L.M.[$] and Sathish Kumar S.[$]
** Lecturer* *[$]Undergraduate students*
Department of Production Engineering, P.S.G College of Technology, Coimbatore
deepaklawrence@ mail.psgtech.ac.in

Abstract: *Modeling and prediction of surface finish of work pieces in machining can play an important role in the automation of manufacturing operations. As surface generation in machining is a complex process, the exact variables and parameters that have to be used for surface roughness prediction models are still under dispute. This work attempts to evaluate and predict surface roughness during turning operation using artificial neural network and multiple regression analysis. In addition to the conventional cutting conditions like cutting speed, feed and depth of cut, this work also used cutting force ratio, cutting time and flank wear of the cutting tool to train the predictive models. The developed models were found to be capable of better predicting the surface roughness with very minimum RMS error and high correlation coefficient compared to earlier works.*
Key words: *Surface Roughness - Flank wear - Back Propagation Neural Network – Multiple Regression Analysis.*

1. INTRODUCTION

Surface characteristics on a microscopic scale is vitally important with regard to load bearing capacity, lubrication, wear, fatigue and corrosive resistance, friction, heat and electric conductivity and visual appearance of mechanical parts. (Doebelin, 2004). Achieving the desired surface quality is of great importance for the functional behavior of a part. At the same time excessively better surface finish may involve more manufacturing cost. Therefore, surface roughness has been the subject of experimental and theoretical investigations for many decades.

Recently (Benardos & Vosniakos 2003) have given a review on the various prediction models on surface roughness done by various researchers in the last several decades. In an earlier work, (Azouzi & Guillot 1997) examined the feasibility of neural network based sensor fusion technique to estimate the surface roughness and dimensional deviations during machining. That study concludes that depth of cut, feed rate, radial and z-axis cutting forces are the required information that should be fed into neural network models to predict the surface roughness successfully. (Risbood et al., 2003) used radial vibration of the tool holder, in addition to conventional cutting conditions as an input parameter for neural network. They did experiment separately for dry and wet cutting conditions and during their experiments they observed that surface finish first improves with increasing feed but later it starts deteriorate with increase of feed. (Lee & Chen 2003) proposed an online surface roughness recognition system using neural networks by monitoring the vibrations caused by the tool and work piece motions during machining.

Tugrul Ozel & Yigit Karpat (2002) used neural network and regression analysis to predict the surface roughness and tool wear in finish hard turning. (Ezugwu et al, 2005) developed an artificial neural network model for the analysis and prediction of the relationship between cutting and process parameters during high-speed turning of nickel-based alloy.

It has been observed that all the above mentioned works have not incorporate flank wear of the cutting tool as an input to train the predictive models even though flank wear can also be an important parameter that influences the surface finish of the work piece. The objective of this paper is to predict surface roughness of turned components using back propagation neural network and multiple regression analysis by training the predictive models using speed(s), feed(f), depth of cut(d), cutting time(t), measured flank wear(Vb) and cutting force ratio (feed force,Fc to tangential force,Ft) during the turning process. The turning experiments have been conducted for 27 different cutting conditions and for each experiment the corresponding flank wear, cutting forces and surface roughness were measured for training and testing the Back Propagation Neural Network and Multiple Regression predictive models.

2. EXPERIMENTAL WORK

For the turning experiment AISI 1045 steel was used as the work material and single point tool of High Speed Steel (HSS) M2 type as the tool material. The tool was ground to specified angles 6 - 9 - 7 - 8 - 15 - 15 - 1.5 as per American Standard Association (ASA) tool signature and the speed, feed and depth of cut for this work- tool combination were selected from the Machining data manual [CMTI, 2004]. The values used are cutting speed 350 - 600 rev/min, feed 0.25 - 0.35 mm/rev and depth of cut 0.5 - 1.0mm. During turning process (PSG A124 lathe), a turning dynamometer (Syscon Instruments) was used for measuring feed force (Fc) and tangential force (Ft). Flank wear was measured using optical profile projector with a magnification of 50X and Surtronic surface roughness tester (Taylor Hobson) was used for measuring the Ra value with a cut-off length of 0.8 mm and an evaluation length of 4 mm , (ISO 4288). The block diagram of the experiment is shown in the Fig. 1 and the experimental arrangement is shown in the Fig 2. Machining was carried out for 27 different cutting conditions (dry cutting) and the corresponding cutting forces, flank wear and surface rough ness were measured and are given in the Table 1.

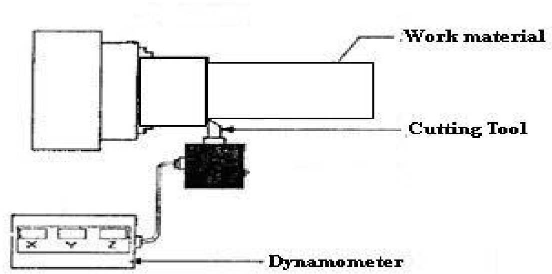

Fig. 1. Schematic Diagram of the Experimental Arrangement

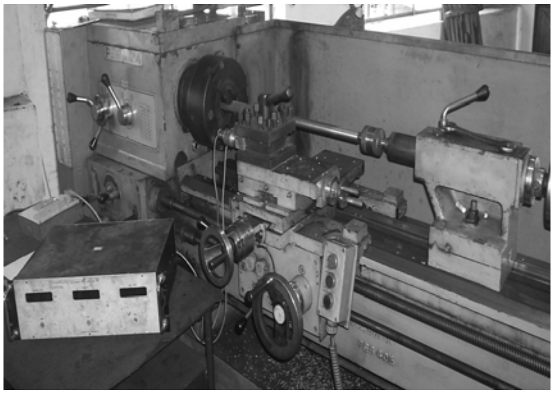

Fig. 2. Experimental set up

Table 1. Experimental conditions and results

Exp. No.	s rpm	f mm/rev	d mm	Ft N/mm^2	Fc N/mm^2	FR Fc/Ft	t sec	V_B mm	Ra µm
1	350	0.25	0.5	451	205	0.45	519	0.042	5.82
2	350	0.25	0.75	440	210	0.47	517	0.11	5.61
3	350	0.25	1	450	211	0.46	509	0.205	5.38
4	350	0.3	0.5	440	201	0.456	429	0.06	5.29
5	350	0.3	0.75	456	206	0.451	423	0.102	5.11
6	350	0.3	1	450	215	0.47	421	0.221	5.06
7	350	0.35	0.5	461	235	0.51	368	0.072	4.89
8	350	0.35	0.75	464	246	0.53	364	0.116	4.72
9	350	0.35	1	459	238	0.51	365	0.213	4.65
10	490	0.25	0.5	460	215	0.46	367	0.038	4.57
11	490	0.25	0.75	446	218	0.49	364	0.123	4.42
12	490	0.25	1	451	228	0.51	363	0.206	4.12
13	490	0.3	0.5	453	244	0.54	309	0.079	4.01
14	490	0.3	0.75	449	251	0.56	308	0.146	3.82
15	490	0.3	1	456	223	0.49	304	0.231	3.76
16	490	0.35	0.5	440	259	0.59	264	0.092	3.32
17	490	0.35	0.75	456	246	0.54	262	0.153	3.21
18	490	0.35	1	451	240	0.53	260	0.227	3.13
19	600	0.25	0.5	440	259	0.59	302	0.081	2.92
20	600	0.25	0.75	446	228	0.51	301	0.143	2.81
21	600	0.25	1	451	221	0.49	298	0.261	2.73
22	600	0.3	0.5	452	253	0.56	255	0.102	2.59
23	600	0.3	0.75	449	273	0.61	249	0.172	2.47
24	600	0.3	1	456	246	0.54	247	0.281	2.33
25	600	0.35	0.5	461	235	0.51	217	0.096	2.15
26	600	0.35	0.75	459	270	0.59	215	0.181	2.03
27	600	0.35	1	462	245	0.53	214	0.296	1.95

3. NEURAL NETWORKS

A neural network can be defined as a computing system made up of a number of, highly interconnected processing elements, which possesses information by its dynamic state response to external inputs. The developed neural network model is shown in the fig 3 where the inputs are cutting speed, feed, depth of cut, cutting force ratio, cutting time and flank wear and the output is the surface roughness value. The neural network model was developed using Neu Net Pro 2.3 [Cor Mac Technologies, 2005], a neural network software. Out of the 27 cutting conditions randomly selected 20 were used for training the back propagation neural network with a topology: 6 – 7 – 1.

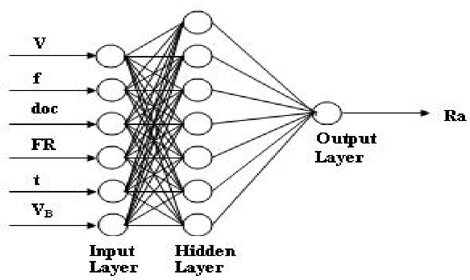

Fig. 3: Neural Network Model Structure

4. REGRESSION ANALYSIS

Regression analysis is a part of statistics that deals with the investigation of the relationship between two or more variables [Douglas, 2003]. Multiple regression and modeling use more than one independent variable to estimate the dependent variable and, in this way attempt to increase the accuracy of the estimate. The general multiple regression estimating equation can be given in equation (1),

$y = a + b_1x_1 + b_2x_2 + ….. + b_kx_k$-------------(1)

where y = dependent variable, $x_{1,}x_{2,........}x_k$ = the independent variables, a = Y – intercept and b_1, b_2….b_k are the slopes associated with x_1, x_2, x_3 … x_k respectively. Regression analysis in this paper has been done using Systat 11 [Systat Software, 2004]. The multiple regression equation obtained for prediction of surface roughness is given in the equation (2),

$$Ra = [(16.147) – (0.013 \times s) – (12.839 \times f) – (0.466 \times d) – (0.991 \times FR) – (0.451 \times V_B) – (0.004 \times t)] \quad … \quad (2)$$

5. RESULTS

The efficiency of developed Neural Network and Regression model were compared for a random set of 7 readings from the experimented values for which the predictive models have not been trained. The coefficient of correlation value was obtained based on the graphical plot of the predicted and measured values of surface roughness for all the seven cutting conditions It was found to be 0.9970 for neural network model and 0.9979 for multiple regression model. RMS Error was calculated by using the formula as given in the equation 3, where n is the number of experiments.

$$\%\ \text{RMS Error} = \sqrt{1/n \sum (\text{measured} - \text{predicted} / \text{measured} \ \text{x}\ 100)^2} \quad \text{----}\ (3)$$

The RMS error value for neural network model was 2.01 % with incorporation of flank wear and the error has increased to 4.145% without incorporating the flank wear of the cutting tool. Similarly for regression model, RMS error was 2.84% with incorporation of flank wear and it has increased to 8.79% without including flank wear of the cutting tool in the training set. This clearly indicates the importance of incorporating tool flank wear in the surface roughness predictive models .The values predicted by neural network and regression analysis along with the actual experimental values are shown in the Table 2. The graphical plot, sample coefficient of determination and the equations connecting the measured and predicted values of surface roughness are shown in the Fig 4 and Fig 5.

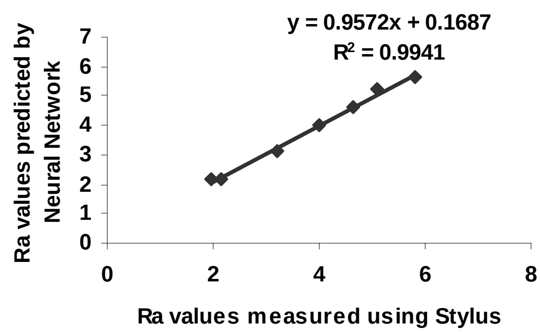

Fig. 4: Comparison between measured and predicted Ra values by Neural Network

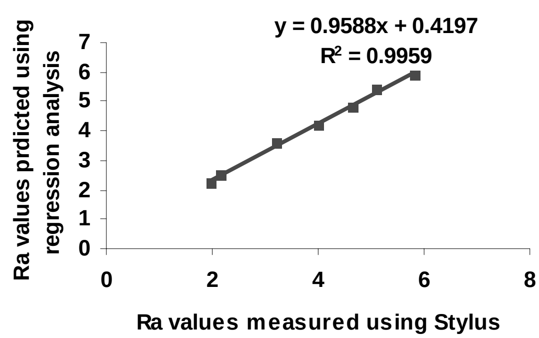

Fig. 5: Comparison between measured and predicted Ra values by Regression Analysis

Table 2. Surface Roughness values predicted by Neural net work and Regression analysis

Ex No	Ra Stylus Measured (μm)	Ra Neural Network (μm)	Ra Regression Analysis (μm)
1	5.82	5.70	5.61
5	5.11	5.13	5.21
9	4.65	4.67	4.58
13	4.01	4.09	3.89
17	3.21	3.34	3.29
25	2.15	2.11	2.21
27	1.95	1.97	1.88

7. CONCLUSION

Surface roughness predictive models based on back propagation neural network and multiple regression analysis were developed by including flank wear and cutting forces in addition to the usual cutting parameters like speed, feed and depth of cut to predict surface roughness in turning. From the developed models it was clear that the values obtained by neural network were closer to the measured Ra values and also the RMS error was less in the case of Neural Network than regression analysis. Hence neural network model provided better prediction capabilities than regression analysis for predicting the Surface roughness in turning for this tool work combination. It has also be observed that accuracy of both the predictive models increased with the inclusion of flank wear of cutting tool as an input parameter to train the models. Thus inclusion of tool flank wear in the predictive model was proven to be beneficial for the better predictions of surface roughness with minimum RMS error and high correlation of coefficient compared to earlier works. Efforts should be made in future for the integration of the developed predictive models with the CNC machines for online surface roughness monitoring during the machining stage.

8. REFERENCES

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