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Artificial Neural Network assisted Sensor Fusion model for predicting surface roughness during hard turning with minimal cutting fluid application and its comparison with Regression Model

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Abstract: *Surface roughness is a factor of great importance in the evaluation of cutting performance and it plays an important role in manufacturing processes. Performance parameters such as cutting force, cutting temperature, vibration etc. can be used to predict surface roughness. It is expected that more accurate prediction would be possible if these factors are considered collectively with cutting parameters since each of these factors predict surface roughness in their own characteristic fashion. In this present work, an attempt was made to fuse cutting temperature along with cutting parameters to predict surface roughness during turning of H13 tool steel having a hardness of 45 HRC. A regression model and an artificial neural network model with sensor fusion were developed and their ability to predict surface roughness (R_a) was analyzed. The fusion model developed based on the artificial neural network was found to be superior to the regression model.*

Keywords: *Hard turning, Surface roughness, artificial neural network, regression analysis, Minimal cutting fluid application.*

1. INTRODUCTION

Surface roughness is a vital parameter in assessing the quality of the finished product. Hard turning process is advantageous over traditional process in terms of reduction in cycle time, reduction in production cost and improved surface finish. Manufacturing industries are developing attentions on dimensional accuracy and surface roughness of finished products as they are very much important.

In the hard turning process, there is a high urge to reduce cutting temperature, cutting force and friction so as to reduce tool wear and to improve surface finish. Hence hard turning operation is normally performed under conventional wet cooling.

Besides providing technological benefits, conventional cutting fluids pose environmental problems such as pollution in the shop floor due to chemical break-down of the cutting fluid at high cutting temperature, creation of biologically hazardous environment to operators due to bacterial growth, water pollution and soil contamination during final disposal [1]. People exposed to large quantities of cutting fluids may have skin contact and they may inhale or swallow the mist particles of cutting fluid. The additives present in the petroleum based cutting fluids may cause dermatitis, problems in the respiratory and digestive systems and even cancer due to their toxicity [2]. Handling of cutting fluid may include the pre-treatment and treatment of cutting fluid wastes. The cost of fluid pre-treatment/treatment is sometimes higher than the purchase price of the cutting fluid itself [3].

Enormous usage of cutting fluid in the shop floor increases the presence of oil content in the air which should be kept within the prescribed regulations suggested by occupational safety and health administration [4]. It is found that Europe alone consumes approximately 320,000 tons of metal working fluids every year, out of which at least two thirds need to be disposed [5].

The problems associated with cutting fluids can be completely avoided by using dry machining. But it is very difficult to implement on the existing shop floor as it needs extremely rigid machine tools and ultra hard cutting tools [6]. In order to alleviate the above-mentioned negative effects of cutting fluids, machining with minimal Cutting Fluid Application (MCFA) has been evolved.

In minimal cutting fluid application, extremely small quantities of cutting fluid is injected in the form of

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ultra fine droplets at very high velocity (about100 m/s) into the cutting zone which is also called as pseudo dry turning. For all practical purposes it resembles dry turning in achieving improved surface finish, lower tool wear by maintaining cutting forces and power at reasonable levels [7]

Models related to machining operations are nonlinear in nature. In order to get better and accurate results, analytical models are often subjected to simplifications and assumptions. Artificial intelligence based modeling approaches are suitable for real time applications out of which artificial neural network (ANN) was found to be viable, reliable and attractive approach [8, 9] due to certain characteristics:

- ANN is suitable for handling nonlinear form of inputs and outputs
- ANN is more successful when compared to conventional approaches.
- Any number of configurations can be developed to obtain a better predicted value of the output.

O¨ zel and Karpat used neural network model to predict surface roughness and tool flank wear during finish hard turning [10]

Feng and Wang studied the influence of workpiece hardness, feed, tool point angle, depth of cut, spindle speed and cutting time on the surface roughness during turning of 8620 steel of hardness 86HRB with carbide inserts having multiphase coatings and they developed a model using nonlinear regression analysis with logarithmic data transformation [11].

Leo and Varadarajan developed a model based on Artificial Neural Network to simulate surface milling of hardened AISI4340 steel with minimal fluid application [12].

From the literature review, it was found that ANN and regression models have been successfully applied by the researchers for modeling surface roughness in hard turning process but very few works are reported on the modeling of surface roughness in hard turning with minimal cutting fluid application. In the present work an attempt was made to fuse the cutting temperature signals with the cutting parameter signals using a neural network and regression model to predict surface roughness. It was found that the predictions made by ANN assisted sensor fusion model matched well with the experimental results.

2. SELECTION OF WORK MATERIAL

The work-piece material that was used for this experiment was H13 tool steel of hardness 43 HRC. This material has got good amount of applications in die casting. Bars of 70 mm diameter and 360 mm length were used in the present experimental work. The chemical composition of the workpiece is tabulated in Table 1

3. SELECTION OF TOOL

The cutting tool inserts and the tool holder were selected as per the recommendations of M/s TaeguTec India (P) Limited who are extending their technical support for this research work.

Table 1 Chemical composition of H13 steel (wt %)

C	Mn	Si	P	Cr	Mo	Fe
0.43	0.214	1.08	0.033	5.02	1.13	balance

The tool insert used for the present experimentation was SNMG 120408 and tool holder used was PSBNR 2525 M12.

4. FORMULATION OF CUTTING FLUID

Since the quantity of cutting fluid used is extremely small and the cutting fluid need to perform both cooling and lubrication, a specially formulated cutting fluid was employed in this investigation. The base of the cutting fluid was a commercially available mineral oil and the formulation contained other ingredients [13]. It acted as oil in water emulsion.

5. EXPERIMENTATION

Kirloskar Turn master-35 lathe was used in the experimental work and the photograph of the lathe is shown in Fig. 1.

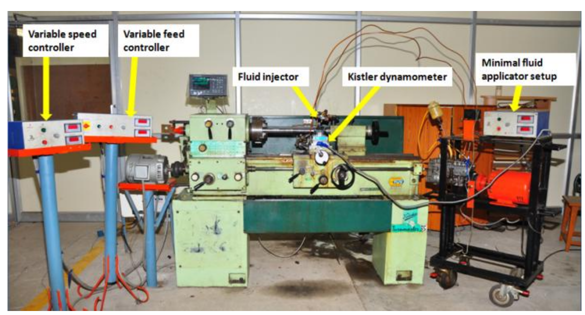

Figure 1: Experimental set up contains lathe and Minimal Fluid application system

The cutting parameters were selected and their combinations were determined and set at semi finish turning range based on the results of preliminary experiments and the recommendations of M/s TaeguTec India (P) Ltd. Table 2 shows the levels of feed rate, cutting speed and depth of cut. During each experiment, surface roughness and cutting temperature were recorded. Surface roughness was measured using Mitutoyo (SJ-210) portable surface roughness tester and cutting temperature was measured using Amprobe (IR 750) Infrared thermometer.

Table 2: Levels of feed rate, cutting speed, and depth of cut

Feed rate (mm/rev)	0.05, 0.075, 0.1
Cutting speed (m/min)	75, 95, 115
Depth of cut (mm)	0.5 , 0.7 , 1

6. DESIGN OF EXPERIMENTS

A 27 run experiment was designed based on Taguchi technique and the cutting parameters namely feed rate, cutting speed and depth of cut were varied at three levels. The experimental work was conducted with two replications. The fluid application parameters, namely pressure at the injector, frequency of pulsing, composition of cutting fluid and rate of application of cutting fluid were maintained at 100 bar, 500 pulses/min, 30% oil in water and 8 ml/min respectively [7]. Table 3 shows the experimental conditions and results of L_{27} orthogonal array.

7. SENSOR FUSION USING R EGRESSION ANALYSIS

An attempt was made to fuse the signals of cutting temperature along with feed rate, cutting speed and depth of cut using linear and nonlinear regression models. It was expected that sensor fusion can predict the surface roughness more accurately with less amount of standard error as the greater the number of symptoms for prediction, will give accurate results on root cause. During regression analysis equations were generated for linear and nonlinear regression models with and without cutting temperature.

Equation (1) presents a linear regression model when temperature was not taken into consideration for predicting the surface roughness; Equation (2) presents linear regression model when temperature was included Equation (3) presents a nonlinear regression model when temperature was not considered and Equation (4) presents a nonlinear regression model when temperature was considered.

$$R_a = [(7.6922755811\ .f) + (6.3601548X10^{-3}\ .v) + (0.34697631\ .d)] \quad (1)$$

$$R_a = [(9.16136586\ .f) + (7.8387880911X10^{-3}\ .v) + (0.532617685\ .d) + (-2.882169339X10^{-3}\ .T_c)] \quad (2)$$

$$R_a = \exp[(5.10317599\ .f) + (3.8413411033X10^{-3}\ .v) + (0.193348891\ .d) + (-0.5345338)] \quad (3)$$

$$R_a = \exp[(6.2847108693\ .f) + (4.38228856X10^{-3}\ .v) + (0.3500779021\ .d) + (-2.439242806X10^{-3}\ .T_c) + (-0.461989699)] \quad (4)$$

Table 3: Experimental data collected during 27 run experiment

S.No	f (mm /rev)	v (mm/ min)	d (mm)	R_a (µm)	Temp (°C)	Training/ testing
1	0.05	75	0.5	1.28	120	Training
2	0.05	75	0.75	1.1	135	Training
3	0.05	75	1	1.58	90	Training
4	0.05	95	0.5	0.91	138	Training
5	0.05	95	0.75	1.03	133	Training
6	0.05	95	1	1.13	137	Training
7	0.05	115	0.5	1.38	145	Training
8	0.05	115	0.75	1.34	137	Training
9	0.05	115	1	1.45	166	Testing
10	0.075	75	0.5	1.19	106	Training
11	0.075	75	0.75	1.09	136	Training
12	0.075	75	1	1.48	153	Training
13	0.075	95	0.5	1.45	114.7	Training
14	0.075	95	0.75	1.86	117	Training
15	0.075	95	1	1.82	153	Testing
16	0.075	115	0.5	1.43	96	Training
17	0.075	115	0.75	1.7	121	Training
18	0.075	115	1	1.65	134	Training
19	0.1	75	0.5	1.64	139	Testing
20	0.1	75	0.75	1.13	140	Training
21	0.1	75	1	1.78	179	Training
22	0.1	95	0.5	1.77	121	Training
23	0.1	95	0.75	1.83	149	Training
24	0.1	95	1	1.53	155	Training
25	0.1	115	0.5	1.32	128	Testing
26	0.1	115	0.75	1.6	158	Training
27	0.1	115	1	1.79	201	Training

In equations (1) to (4), R_a represents surface roughness, f represents feed rate, v is the cutting speed, d is the depth of cut and T_c is the cutting temperature. Table 4 compares the coefficient of determination and stand errors associated with linear and nonlinear regression models with and without considering cutting temperature. Values of unknown coefficients found in equation (1) to (4) and coefficient of determination were determined using Data Fit 9.0 software.

Table 4. Comparison of coefficient of determination and standard errors associated with regression models

Model	Type	Parameters	Coefficient of determination	Standard error
Model 1 (Equation (1)	Linear	f,v,d	0.90027	0.20326
Model 2 (Equation (2)	Linear	f,v,d,T_c	0.87504	0.19505
Model 3 (Equation (3)	Non linear	f,v,d	0.85748	0.20387
Model 4 (Equation (4)	Non linear	f,v,d,T_c	0.9559	0.19411

Coefficient of determination is the statistical measure of how well the regression model matches the real data points. A coefficient of determination of 1.0 indicates that the regression model perfectly matches the data points. In the present investigation on the four regression models, nonlinear regression model in which temperature was taken in to consideration (model 4) was taken into consideration as it offered the lowest standard error and the highest coefficient of determination.

The nonlinear regression model developed was tested with the testing data available in table 3. The results were compared with experimental results and presented in table 5. Table 5 Testing and comparison of surface roughness predicted by the nonlinear regression with experimental results

Testing data				Surface roughness R_a (μm)		
f (mm/rev)	v (m/min)	d (mm)	T_c (ºC)	Exp. result	Non linear regression with temperature	% Error
0.05	115	1	166	1.45	1.35	6.89
0.075	95	1	153	1.82	1.59	12.63
0.1	75	0.5	139	1.64	1.49	9.14
0.1	115	0.5	128	1.32	1.50	13.63

8. ARTIFICIAL NEURAL NETWORK MODEL WITH SENSOR FUSION

It is reported that a sensor fusion model based on ANN can predict the results better than regression based models [10]. Accordingly, an attempt was made to develop an ANN model to fuse cutting temperature along with feed rate, cutting speed and depth of cut. The architecture for the artificial neural network was selected through an exhaustive examination of a number of network configurations. This was done by changing the number of neurons in the hidden layer and the number of hidden layers.

A back propagation algorithm, which adjusts weights according to the gradient descent method [14] was used to minimize the difference between the desired output and actual output of the network. A routine which utilizes a feed forward back propagation algorithm was used in developing this model [14]. The process of updating the value of weights and biases of the algorithm was easily made with the assistance of the Matlab ANN toolbox. The guidelines given by Zhang et al. [15] were also considered. According to Zhang et al, the recommended number of nodes for the hidden layer are 'n/2', '1n', '2n', and '2n + 1' where n is the number of input nodes. Since the number of input variables in this study 3, the recommended number of nodes in the hidden layer are (4)/2 = 2, 1(4) = 4, 2(4) = 8, and 2(4) + 1 = 9. Therefore, this study was applied to eight different network structures, which are 4–2–1, 4–4–1, 4–8–1, 4–9–1, 4–2–2–1, 4–4–4–1, 4–8–8–1 and 4–9–9–1, apart from 52 other configurations for the prediction of surface roughness.

In this present investigation, 'trainlm' was considered as the training function and 'learngdm' as the learning function. The transfer function of the ANN model was considered as "tansig" and the sigmoid function that was used in this experimentation is shown in equation (5)

$$f(x) = \frac{1}{1+e^{-x}} \qquad (5)$$

The hidden layer type was altered into single and multi layer types with different neuronal values using trial and error method [15] for the best configuration with least MSE error value and better coefficient of determination.

9. SURFACE ROUGHNESS PREDICTION BY ANN

Out of the 27 readings in table 3, 23 readings were used for training the model and 4 readings were used for testing the model and this ratio between the number of training values to the number of testing values was chosen based on similar work [8, 9].

The network was created with 4 neurons in the input layer and one neuron in the output layer. Networks with varying architecture were trained for a fixed number of cycles and were tested using a set of input and output parameters. The number of hidden layers and number of neurons in the hidden layer was changed progressively. The root mean square error (RMSE) was considered as quadratic scoring rule for the measurement of average magnitude of the error. RMSE is more useful when large errors are particularly undesirable [16].

ANN model was trained with 60 different configurations by considering the temperature and the hidden layers were altered into single and multi layers with different number of neurons and RMSE values and coefficient of determination values were calculated. Out of the 60 different architectures, the configurations which gave lower MSEs are shown in Fig. 2.

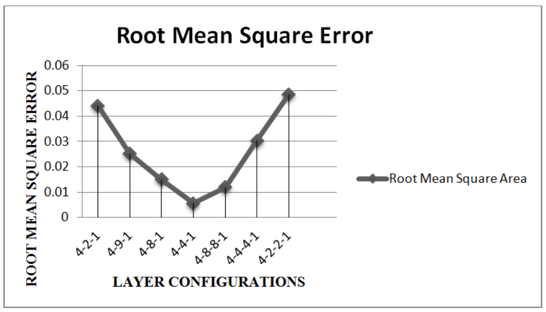

Figure 2: Variation of limiting MSE with different layer configuration

The least MSE value was found to be 4-4-1 with an MSE error of 0.005 at 10000 cycles. The coefficient of determination for this configuration was found to be 0.97826. The 4-4-1 architecture of ANN model is shown in Fig. 3.

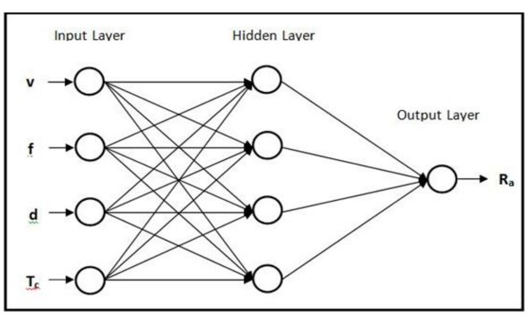

Figure 3: The 4-4-1 architecture of the ANN model

The ANN model with architecture 4-4-1 was tested with the testing data available in table 3. The results were compared with experimental results and presented in table 6.

The coefficient of determination and the standard error for the ANN model with sensor fusion and nonlinear regression model are presented in table 7.

Table 6 Testing and comparison of surface roughness predicted by ANN model with temperature and experimental results

Testing data				R_a (µm)		
f (mm/ rev)	V (m/ min)	d (mm)	T_c (°C)	Experimental result (µm)	ANN model with temperature	% Error
0.05	115	1	166	1.45	1.411	2.6
0.075	95	1	153	1.82	1.761	3.2
0.1	75	0.5	139	164	1.615	1.5
0.1	115	0.5	128	1.32	1.28	2.98

Table 7: Coefficient of determination and standard error for ANN and nonlinear regression model

Model	Standard error	Coefficient of determination
Nonlinear regression model with temperature	0.17161	0.9559
ANN model with temperature	0.04250	0.97826

10. RESULTS AND DISCUSSION

In the present investigation cutting temperature was considered along with the cutting parameters such as feed rate, cutting speed and depth of cut to predict surface roughness. It was observed that better prediction is possible when cutting temperature is considered collectively along with the cutting parameters. It was also found that nonlinear regression model could fuse the symptoms of surface roughness better than linear regression model. When the cutting parameters alone were considered, the coefficient of determination was 0.90027 for the linear regression model where as it was 0.9559 in nonlinear regression model when cutting temperature was also considered along with the cutting parameters. The comparison between ANN model with sensor fusion and nonlinear regression model with sensor fusion is presented in table 7 clearly revealed that ANN model developed by considering cutting temperature along with cutting parameters predicted better results than the predictions by nonlinear regression model with sensor fusion. From table 7, it was found that standard error was reduced by 75.23 % and the coefficient of determination was improved by 2.04 % when temperature was fused with cutting parameters in ANN model.

11. CONCLUSIONS

In the present study, regression and ANN approaches were used for the prediction of surface roughness during hard turning of H13 tool steel with minimal cutting fluid application. The data obtained by means of L_{27} orthogonal array were used to develop the models. The following conclusions were drawn from the present study:

1. Surface roughness can be predicted better by considering more symptoms along with cutting parameters.
2. A fusion model based on ANN can predict surface roughness better than regression models.
3. Minimal cutting fluid application technique promoted green environment in the shop floor, minimized the industrial hazard and usage of large quantity of cutting fluid.

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