DEVELOPMENT OF EMPIRICAL MODEL FOR PREDICTION OF SURFACE ROUGHNESS USING REGRESSION & ANN METHOD

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ABSTRACT
In this present work, the important challenge is to manufacture high quality and low cost products within the stipulated time. The quality is one of the major factors of the product which depends upon the surface roughness and hence the surface roughness placed an important role in product manufacturing. Hence, an Empirical model is proposed for prediction of surface roughness in machining processes at given cutting conditions. The model considers the following working parameters spindle speed, feed, depth of cut, number of flutes and overhang of the tool. For a given work-tool combination, the range of cutting conditions are selected from different cutting condition variables. The experiments were conducted based on the principle of Factorial Design of Experiment (DOE) method with mixed level. After conducting experiments, surface roughness values are measured. Then these experimental results are used to develop an Empirical model for prediction of surface roughness by using Multiple Regression method. In this the Artificial Intelligence based neural network modelling approach is presented for the prediction of surface roughness of Aluminium Alloy products machined on CNC End Milling using High speed steel tool. Trails were made with different combinations of step size and momentum to select the best learning parameter. The best network structure with least Mean Square Error (MSE) was selected among the several networks. The multiple regression models, which are most widely used as prediction methods, are considered to be compared with the developed Artificial Neural Network (ANN) model performance.

KEYWORDS: *Surface Roughness, Factorial Design of Experiments, Prediction Models and Artificial Neural Network.*

I. INTRODUCTION

Surface Roughness is one of the important attributes of job quality in machining process. Milling is the most common metal removal operation and it is widely used in a variety of manufacturing industries including the aerospace and automotive sectors, where quality is an important factor in the production of slots, pockets, precision molds and dies. The quality of the surface plays a very important role and a good-quality machined surface significantly improves fatigue strength, corrosion resistance, or creep life [1]. Therefore, the desired finish surface is usually specified and the appropriate processes are selected to reach the required quality.
Several factors influence the final surface roughness in any machining operation [2]. Factors such as Spindle Speed, Feed Rate, Depth of Cut, Number of flutes, over hanging length that controls the cutting operation can be setup in advance. However, factors such as geometry of cutting tool, tool wear and material properties of both tool and work piece are uncontrollable. One should develop

techniques to predict the surface roughness of a product before milling in order to determine the requirement of machining parameters such as feed rate and spindle speed for obtaining a desired surface roughness and increasing product quality.

II. LITERATURE SURVEY

This surface roughness might be considered as the sum of two independent effects. K. Taraman et.al. developed [1] a mathematical model for the surface roughness in a turning operation. R. M. Sunderam et. al., [2] has presented the experimental development of mathematical models for predicting the surface finish of AISI 4140steel in fine turning operation using TiC coated tungsten carbide throw away tools. M.S. Chua [3] et. al., developed a process planning or NC part programming, optimal cutting conditions are to be determined using reliable mathematical models representing the machining conditions of a particular work-tool combination. Dr. Mike S. Lou [4] the author examined a new approach for finish surface prediction in end-milling operations. Used parameters spindle speed, feed rate, depth of cut. In order to develop a new technology for surface prediction, literature review of the surface texture, surface finish parameters and multiple regression analysis have been carried out. B. Sidda Reddy [5], This paper deals with the development of second order mathematical model using Response Surface Methodology (RSM) to predict the surface roughness in terms of machining parameters cutting speed, feed rate and depth of cut. The experimentation has been conducted using full factorial design in the design of experiments (DOE) on CNC turning machine with carbide cutting tool. This study deals with the development of a surface roughness prediction model for machining aluminium alloys using multiple regression and artificial neural networks. D. Hanumantha Rao [6] In this present investigation , a hybrid ANN Genetic Algorithm model is developed for predicting the SDAS values in aluminium alloy casting, Adaptation and optimization of network weights using GA is proposed as a mechanism to improve the performance of ANN model. P. Nanda Kumar [7] in this paper Al based neural network modelling approach is presented for the prediction of surface roughness of aluminium alloy products machined on CNC turning centre. Trails were made with different combinations of step size and momentum to select the best learning parameter. The best network structure with least MSE was selected among the several networks. The multiple regression models, which are most widely used as prediction methods, are considered to be compared with the developed ANN model performance. Above all the works done by Researches & Scientists considers only three working parameters mainly such as spindle speed, feed, and depth of cut from 1994 to 2013. Till time no one considers more three working parameters. All the research works cannot reach the maximum surface roughness values. This is the base for my project work by considering five parameters spindle speed, feed, depth of cut, number of flutes, and overhang length of the tool for achieving good surface values with less percentage deviation from actual.

III. DESIGN OF EXPERIMENTS

The factors considered were Cutting Speed, Feed Rate, Depth of Cut, Number of flutes and over hanging Length. The range of values of each factor was set at the three levels, namely low, medium and high, as shown in Table 1.

Table 1. Values of test variables

Variables Designation	Description	Values at different levels		
		Low (L)	Medium M)	High (H)
V	Cutting Speed(rpm)	2000	2500	3000
F	Feed rate (mm/min)	160	-	240
D	Depth of cut(mm)	0.5	-	0.8
Nf	Number of flutes	2	-	4
Ol	Overhanging length(mm)	30	-	35

The number of experiments to be carried out was planned using a full factorial design [3*2*2*2*2][3,4]. Based on this setting, a total of 48 experiments, as shown in Table 2, were carried out. The experiments are conducted on CNC Milling and selected work piece material is 6082-

Aluminium alloy (Si-0.6 to 1.3, Fe-0.6, Cu-0.1, Mn-0.4 to 1.0, Cr-0.25, Zi-0.1, Ti-0.2, and Mg-0.4 to 1.2). The cutting tool with carbide inserts (CCMW 9030) is used to machine the work piece material. The response of surface roughness was measured by using Mitutoyo Surftest-211 instrument and the results are tabulated in table 2.

Table 2: Experimental Results (Train Data)

Test No.	v(rpm)	f(mm/rev)	d (mm)	nf	ol (mm)	Ra (μm)	Test No.	v(rpm)	f(mm/rev)	d (mm)	nf	ol (mm)	Ra (μm)
1	2000	160	0.5	2	35	1.747	**25**	2000	160	0.5	4	35	4.777
2	2000	160	0.8	2	35	1.537	**26**	2000	160	0.8	4	35	4.773
3	2000	240	0.8	2	35	1.717	**27**	2000	240	0.8	4	35	7.087
4	2000	240	0.5	2	35	1.563	**28**	2000	240	0.5	4	35	6.31
5	2500	160	0.5	2	35	1.46	**29**	2500	160	0.5	4	35	3.947
6	2500	160	0.8	2	35	1.513	**30**	2500	160	0.8	4	35	4.403
7	2500	240	0.8	2	35	1.677	**31**	2500	240	0.5	4	35	5.393
8	2500	240	0.5	2	35	1.653	**32**	2500	240	0.8	4	35	5.75
9	3000	160	0.8	2	35	0.823	**33**	3000	160	0.8	4	35	3.213
10	3000	160	0.5	2	35	0.587	**34**	3000	160	0.5	4	35	2.797
11	3000	240	0.8	2	35	1.623	**35**	3000	240	0.8	4	35	2.707
12	3000	240	0.5	2	35	1.657	**36**	3000	240	0.5	4	35	2.54
13	2000	160	0.8	2	30	2.497	**37**	2000	160	0.8	4	30	2.04
14	2000	160	0.5	2	30	2.49	**38**	2000	160	0.5	4	30	2.353
15	2000	240	0.5	2	30	3	**39**	2000	240	0.5	4	30	2.847
16	2000	240	0.8	2	30	4.07	**40**	2000	240	0.8	4	30	3.167
17	2500	160	0.5	2	30	1.58	**41**	2500	160	0.8	4	30	1.21
18	2500	160	0.8	2	30	1.5	**42**	2500	160	0.5	4	30	0.97
19	2500	240	0.5	2	30	4.193	**43**	2500	240	0.8	4	30	2.437
20	2500	240	0.8	2	30	4.057	**44**	2500	240	0.5	4	30	2.73
21	3000	160	0.5	2	30	2.55	**45**	3000	160	0.8	4	30	0.947
22	3000	160	0.8	2	30	2.493	**46**	3000	160	0.5	4	30	1.257
23	3000	240	0.8	2	30	3.86	**47**	3000	240	0.5	4	30	2.86
24	3000	240	0.5	2	30	4.26	**48**	3000	240	0.8	4	30	3.203

IV. SURFACE ROUGHNESS MODEL

The purpose of developing the mathematical models relating the machining responses and their machining factors is to facilitate a functional relationship between surface roughness and the independent variables (v, f, d, nf, ol). The following models are considered in this section.

4.1 Multiple Regression Model

The multiple regression models were developed by using the independent variables (v, f, d, nf, ol) and the dependent variable (Ra). The experimental results were modeled using multiple regression methodology and respective models excluding and including interaction terms were developed.
The equation excluding interaction terms using independent variables [5].
For simplicity, equation is re-written as algebraic representation of regression line can be represented by

Ra = b0+b1x1+b2x2+b3x3+b4x4+b5x5 ……………(1)

Where, Ra is surface roughness; x1,x2,x3,x4,x5 are predictors and b0,b1,b2,b3,b4,b5 are the regression coefficients.
Using the experimental data, the analysis consisted of estimating these five variables first for first order model. If the first order model demonstrates any statistical evidence of lack of fit, a second order model can then be developed using additional data, this model is an algebraic model with interaction terms are considered. The Multiple regression equation of second order model with interaction terms can be represented by the fallowing equation.

R=b0+b1x1+b2x2+b3x3+b4x4+b5x5+b6x1x2+b7x1x3+b8x1x4+b9x1x5+b10x2x3+b11x2x4+b12x2x5+b13x3x4+b14x3x5+b15x4x5+b16x12+b17x22+b18x32+b19x42+b20x52 …………………..(2)

Where b0,b1,b2,b3,b4,b5,b6,b7,b8,b9,b10,b11,b12,b13,b14,b15,b16,b17,b18,b19,b20 are the multiple regression coefficients.

4.2 Artificial Neural Networks Model (ANN)

ANN is a system of processing units called neurons (or nodes), which are distributed over a finite number of layers and interconnected in a predetermined manner to accomplish a desired task. ANN architecture is made up of an input layer, one or more hidden layers and an output layer. General ANN structure is shown in Fig 1. The hidden and an output layer have processing elements and interconnections called neurons and synapses respectively.
Each interconnection has an associated connection strength or weight. The number of hidden layers and that of the nodes in each layer have to be decided very carefully, because the system cannot model the given information if it has too few hidden layer units [6]. However, too many hidden units limit the networks ability to generalize the results, so that the resulting model would not work well for few incoming data.

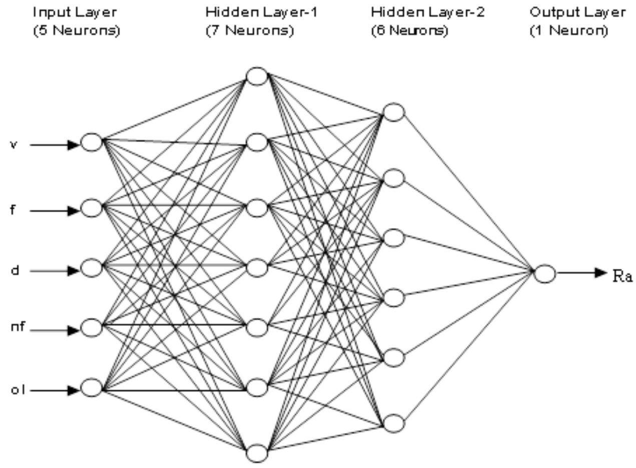

Figure 1: Typical Neural Network Model

Each processing element first performs a weighted accumulation of the respective input values and then passes the result through an activation function. Expect 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. The output of node in layer can be obtained by the equation (3).

O_j^k = f(net_j^k) = 1/(1+e-(natkj)) ………………..(3)

where, $net_j^k = \sum w_{ji}^k o_i^{k-1}$

Where, weight wkji is in between the ith neuron in the (k-1)th layer and the jth neuron in the kth layer, f(.) is the activation function and okj is the output of the jth neuron in the kth layer [7].

V. DEVELOPMENT OF SURFACE ROUGHNESS PREDICTION MODEL

The experimental results as shown in the Table 2 are used to develop the surface roughness prediction model. The criterion to judge the efficiency and the ability of the model to predict surface roughness values is taken as percentage deviation(Δ) which is defined in equation(4). With this criterion it would be much easier to see how the proposed model fit and how the predicted values are close to the actual ones.
Percentage Deviation = ((Predicted Ra – Experimental Ra)/Experimental Ra)*100 ……………..(4)

5.1 Multiple Regression Model

Regression analysis is conducted with MINITAB using above experimental data to establish the surface roughness prediction model.

5.1.1 First Order Multiple Regression Model:

The First Order Multiple Regression Model for the prediction of surface roughness is postulated by the equation (1) and the fallowing equation is found

In Ra = -1.94 -0.000912v+0.0140f+0.39d+0.534nf+0.0724ol ……………….(5)

Referring to the regression analysis results in Table 4, for 5-degrees of freedom for regression and 42 degrees of freedom for residual error, F-ratio from the regression analysis is 4.54, which is greater than F-ratio (2.41) from the statistical tables. Its P-value corresponding to F-ratio is 0.002, which is significant for 95% confidence interval. All the independent variables are not significant as their p-value are less than 0.05. The R2 value is 35.1%, which indicates 35.1 variability in predicting Ra with independent variables. Hence, the first order multiple regression model cannot be considered. In order to improve the prediction accuracy and for further comparison, another model called second order multiple regression model is considered.

5.1.2 Second Order Multiple Regression Model:

The Second Order Multiple regression model for the prediction of surface roughness is postulated by equation (2) and the following equation is found.

In ***Ra = -6.2+0.0117v+0.0774f-3.69d-10.4nf+0.062ol+0.000001vf-0.00060vd-0.000816vnf-0.000313vol+0.0066fd+0.00093fnf-0.00223fol+0.212dnf+0.111dol+0.389nfol+0.000000v2……(6)***

If the purpose is to determine the factors and factor interaction are statistically significant in predicting Ra based on 95% confidence interval, the p-value of all the independent variables must be below 0.05. The regression analysis results are shown in Table 5.

The p-values are greater than 0.05 except for v, f, nf, vnf, vol, fol, nfol. The independent variables with largest p-values are eliminated one in each stage, until attaining the model with all significant independent variables. The following equation was found after eliminating all insignificant variables.

Ra = -5.46+0.0108v+0.0789f-10.2nf-0.000816vnf-0.000285vol-0.00200fol+0.394nfol………….. (7)

In Table 5,for 7 degree of freedom of regression and 40 degree of freedom for residual error, the F-ratio from the regression analysis is 49.49, which is greater than F-ratio from the statistical tables (2.02) and the corresponding p-value is less than 0.05 i.e. 0.001. Hence the model is significant. All the independent variables are significant since their p-value is less than 0.05 for 95% confidence interval. The R2 value is 89.6, which indicates 89.6% variability in predicting Ra with independent variables.

Table 3. Regression Analysis: In Ra Vs. v, f, d, nf, ol

Regression Analysis without interaction terms
Ra = - 1.94 - 0.000912 v + 0.0140 f + 0.39 d + 0.534 nf + 0.0724 ol

Predictor	**Coef**	**SE Coef**	**T**	**P**
Constant	-1.937	2.979	-0.65	0.519
V	-0.0009123	0.0004522	-2.02	0.050
F	0.014009	0.004616	3.03	0.004
D	0.387	1.231	0.31	0.755
NF	0.5335	0.1846	2.89	0.006
OL	0.07236	0.07385	0.98	0.333

S=1.27915 R-Sq=35.1% R-Sq(adj)=27.3%

Analysis of Varience:

Source	**DF**	**SS**	**MS**	**F**	**P**
Regression	5	37.126	7.425	4.54	0.002
Residual error	42	68.721	1.636		
Total	47	105.847			

Table 4. Regression Analysis: In Ra Vs. v, f ,nf ,vnf ,vol ,fol, nfol

Modified Regression Analysis with interaction terms

Ra = -5.46+0.0108v+0.0789f-10.2nf-0.000816vnf-0.000285vol-0.00200fol+0.394nfol

Predictor	**Coef**	**SE Coef**	**T**	**P**
Constant	-5.456	1.530	-3.57	0.001
V	0.010813	0.001771	6.11	0.000
F	0.07890	0.01996	3.95	0.000
NF	-10.246	1.032	-9.93	0.000
Vnf	-0.0008164	0.0001850	-4.41	0.000
Vol	-0.00028543	0.00005142	-5.55	0.000
Fol	-0.0019967	0.0006114	-3.27	0.002
Nfol	0.39447	0.02828	13.95	0.000

S=0.523343 R-Sq=89.6% R-Sq(adj)=87.8%

Analysis of Variance:

Source	**DF**	**SS**	**MS**	**F**	**P**
Regression	7	94.889	13.556	49.49	0.001
Residual error	40	10.956	0.274		
Total	47	105.845			

The values predicted by first order and second order multiple regression models are tabulated in Table 5. The percentage deviation is computed between the experimental values and predicted values for the train data and results are tabulated in Table 5.

Table 5. Experimental & Regression Model Values

S. No	**Experimental Ra**	**First Order Multiple Regression Ra**	**Second Order Multiple Regression Ra**	**S. No**	**Experimental Ra**	**First Order Multiple Regression Ra**	**Second Order Multiple Regression Ra**
1	1.747	2.27	1.48	**25**	4.777	3.34	5.34
2	1.537	2.39	1.48	**26**	4.773	3.46	5.34
3	1.717	3.51	2.21	**27**	7.087	4.58	6.06
4	1.563	3.39	2.21	**28**	6.31	4.46	6.06
5	1.46	1.82	1.08	**29**	3.947	2.89	4.12
6	1.513	1.93	1.08	**30**	4.403	3.00	4.12
7	1.677	3.05	1.80	**31**	5.393	4.01	4.84
8	1.653	2.94	1.80	**32**	5.75	4.12	4.84
9	0.823	1.48	0.67	**33**	3.213	2.55	2.90
10	0.587	1.36	0.67	**34**	2.797	2.43	2.90
11	1.623	2.60	1.40	**35**	2.707	3.67	3.62
12	1.657	2.48	1.40	**36**	2.54	3.55	3.62
13	2.497	2.03	1.99	**37**	2.04	3.10	1.90
14	2.49	1.91	1.99	**38**	2.353	2.98	1.90
15	3	3.03	3.51	**39**	2.847	4.10	3.42
16	4.07	3.15	3.51	**40**	3.167	4.22	3.42
17	1.58	1.46	2.30	**41**	1.21	2.64	1.39
18	1.5	1.57	2.30	**42**	0.97	2.52	1.39
19	4.193	2.58	3.82	**43**	2.437	3.76	2.91
20	4.057	2.69	3.82	**44**	2.73	3.64	2.91
21	2.55	1.00	2.61	**45**	0.947	2.18	0.89
22	2.493	1.12	2.61	**46**	1.257	2.07	0.89
23	3.86	2.24	4.13	**47**	2.86	3.19	2.41
24	4.26	2.12	4.13	**48**	3.203	3.30	2.41
Percentage Deviation						**47.40**	**16.833**

5.2 Artificial Neural Network Model

Artificial neural networks are non-linear mapping systems and hence can be used to develop the prediction models. Neuron solution (Version 5.0) software has been used for present study. The network selected is a multilayer perception (MLP), which consists of at least three layers. The activation function used is Tan Axon function, which is a nonlinear function.

5.2.1 Training of Artificial Neural Network

The ANN is trained using input with corresponding output data of experimental results.

Training Error:

The training error i.e. MSE (Mean Square Error) is the criterion for obtaining optimum training parameter and network performance. The back propagation of error is continued for a number of iterations (Epochs) until an acceptable error level is achieved. A large number of iterations are required to back propagate the error from the output to input layer. Such process is carried out to adjust the values of weights to achieve certain estimation accuracy. The average Mean Square Error (MSE) can converge to a global or a local minimum. Generally, it is seen that the error is too high at low epochs. The error is decreased rapidly with increase in number of epochs.

Selection of best size and momentum parameter:

Step size (η) affects the training speed. The large η provides rapid learning but might also result in oscillation. The amount of inertia is dictated by the momentum parameter. Certain procedure is adapted to determine the best combination of step size and momentum parameter. The selected network structure is

5-7-6-1 and trained with 48 training patterns with different combinations of step size ranging from 0.2 to 0.8 at an increment of 0.1. The network is trained to 1,000 epochs for all the 49 combinations and the Mean Square Error (MSE) for all the 49 combinations of step size and momentum are summarized in Table 6.

Table 6. Summary of various combinations of Step size and Momentum.

Trail no.	Step size	Momentum	MSE	Trail no.	Step size	Momentum	MSE
1	0.2	0.2	0.003941	**26**	0.5	0.6	0.001687
2	0.2	0.3	0.003821	**27**	0.5	0.7	0.002020
3	0.2	0.4	0.002534	**28**	0.5	0.8	0.002666
4	0.2	0.5	0.003349	**29**	0.6	0.2	0.003045
5	0.2	0.6	0.003580	**30**	0.6	0.3	0.002857
6	0.2	0.7	0.002985	**31**	0.6	0.4	0.002597
7	0.2	0.8	0.002385	**32**	0.6	0.5	0.003002
8	0.3	0.2	0.003243	**33**	0.6	0.6	0.002720
9	0.3	0.3	0.002715	**34**	0.6	0.7	0.002624
10	0.3	0.4	0.002488	**35**	0.6	0.8	0.001903
11	0.3	0.5	0.002591	**36**	0.7	0.2	0.003087
12	0.3	0.6	0.002992	**37**	0.7	0.3	0.002846
13	0.3	0.7	0.002629	**38**	0.7	0.4	0.002644
14	0.3	0.8	0.002915	**39**	0.7	0.5	0.002915
15	0.4	0.2	0.003189	**40**	0.7	0.6	0.002821
16	0.4	0.3	0.003259	**41**	0.7	0.7	0.002091
17	0.4	0.4	0.002996	**42**	0.7	0.8	0.001714
18	0.4	0.5	0.002838	**43**	0.8	0.2	0.002810
19	0.4	0.6	0.002540	**44**	0.8	0.3	0.002868
20	0.4	0.7	0.002568	**45**	0.8	0.4	0.002957
21	0.4	0.8	0.002480	**46**	0.8	0.5	0.001411(LOW)
22	0.5	0.2	0.002238	**47**	0.8	0.6	0.002771
23	0.5	0.3	0.002837	**48**	0.8	0.7	0.002186
24	0.5	0.4	0.002115	**49**	0.8	0.8	0.002340
25	0.5	0.5	0.002991				

The best combination i.e. step size and momentum is selected based on lowest MSE .The least MSE value 0.001411 is shown in table 7.

The best combination set among them is obtained by training the network further in the iterative stages in the step of 5000 and up to 60,000 epochs. The corresponding mean square errors (MSE) at each stage for all the combinations are examined. It was observed that the MSE was continuously decreasing and there was no oscillations in the MSE values for combination set with 0.8 step size and 0.5 momentum. Hence, 0.8 step size and 0.5 momentum values are selected as the best combination learning parameters.

Selection of best Network Structure

The best network is the one, which yields better prediction results. The various possible network structures are to be trained by using the best combination learning parameters. In the present problem, the number of neurons in input layer is 5 (corresponding to 5 independent variables i.e, speed, feed, depth of cut, number of flutes, over hanging length) and the number of neurons in the output layer is 1 (corresponding to the response variable i.e, surface roughness). The different network structures are considered and the number of neurons considered in each hidden layer varies 1 to 8. All the possible combinations of different structures are trained for 1,000 epochs and the corresponding MSE values are as shown in Table 7. It is observed that 5-7-6-1 network structure has the lowest MSE and it is considered for further training.

Table 7. Different ANN structures and their MSE

No. of Hidden Layers	Structure	Number of Epochs	MSE	No. of Hidden Layers	Structur e	Number of Epochs	MSE
Zero	5-0-1	1000	0.03080	**Two**	5-5-5-1	1000	0.001227
One	5-1-1	1000	0.03081	**Two**	5-6-1-1	1000	0.003802
One	5-2-1	1000	0.00439	**Two**	5-6-2-1	1000	0.001679
One	5-3-1	1000	0.00309	**Two**	5-6-3-1	1000	0.001710
One	5-4-1	1000	0.001776	**Two**	5-6-4-1	1000	0.001369
One	5-5-1	1000	0.002279	**Two**	5-6-5-1	1000	0.001775
One	5-6-1	1000	0.002258	**Two**	5-6-6-1	1000	0.001580
One	5-7-1	1000	0.001790	**Two**	5-7-1-1	1000	0.003165
One	5-8-1	1000	0.001056	**Two**	5-7-2-1	1000	0.002823
Two	5-1-1-1	1000	0.03125	**Two**	5-7-3-1	1000	0.001523
Two	5-2-1-1	1000	0.004050	**Two**	5-7-4-1	1000	0.002134
Two	5-2-2-1	1000	0.003612	**Two**	5-7-5-1	1000	0.001754
Two	5-3-1-1	1000	0.003824	**Two**	5-7-6-1	1000	0.000385(LOW)
Two	5-3-2-1	1000	0.003414	**Two**	5-7-7-1	1000	0.001063
Two	5-3-3-1	1000	0.002371	**Two**	5-8-1-1	1000	0.004646
Two	5-4-1-1	1000	0.002875	**Two**	5-8-2-1	1000	0.001499
Two	5-4-2-1	1000	0.001980	**Two**	5-8-3-1	1000	0.002051
Two	5-4-3-1	1000	0.001659	**Two**	5-8-4-1	1000	0.001980
Two	5-4-4-1	1000	0.002219	**Two**	5-8-5-1	1000	0.001034
Two	5-5-1-1	1000	0.005821	**Two**	5-8-6-1	1000	0.000778
Two	5-5-2-1	1000	0.001912	**Two**	5-8-7-1	1000	0.000712
Two	5-5-3-1	1000	0.002121	**Two**	5-8-8-1	1000	0.000839
Two	5-5-4-1	1000	0.001804				

5.2.2 Development of ANN Model

The 5-7-6-1 structure with 0.8 step size and 0.5 momentum parameter is trained further with the increase of epochs step by step with an increment of 5000 epochs.

The training results of MSE in successive steps are tabulated in Table 10.

The Mean Square Error is decreasing gradually with increasing number of epochs in the successive steps and it is observed that the lowest MSE is at 50,000 epochs and it is maintained constant with increasing number of epochs in successive steps of learning process upto 60,000 epochs. The results are predicted at 60,000 epochs and the percentage deviation is also computed and tabulated in Table

8. The experimental values of train data and the values predicted by the first order multiple regression and ANN are tabulated in Table 9 and shown in Fig.2.

Table 8. Training results of 3-8-6-1 structure

S. No.	Epochs	MSE	S. No.	Epochs	MSE
1	1000	3.85E-04	**8**	30000	1.5251E-07
2	2000	7.830E-04	**9**	35000	1.84856E-07
3	5000	9.50664E-05	**10**	40000	2.72734E-09
4	10000	1.60223E-05	**11**	45000	9.37627E-08
5	15000	5.43951E-07	**12**	50000	4.27678E-11(LOWEST)
6	20000	1.69464E-06	**13**	55000	1.43983E-09
7	25000	6.02762E-07	**14**	60000	3.21674E-07

Table 9. Experimental and Predicted Values (Train Data)

Expt. No.	Experimental Ra	ANN Ra	Second Order Multiple Regression Ra	Expt. No	Experimental Ra	ANN Ra	Second Order Multiple Regression Ra
1	1.747	1.74700972	1.48	**25**	4.777	4.7770045	5.34
2	1.537	1.53700814	1.48	**26**	4.773	4.77299458	5.34
3	1.717	1.71699613	2.21	**27**	7.087	7.08703411	6.06
4	1.563	1.5629731	2.21	**28**	6.31	6.31000704	6.06
5	1.46	1.45996153	1.08	**29**	3.947	3.94699335	4.12
6	1.513	1.51299949	1.08	**30**	4.403	4.40299972	4.12
7	1.677	1.67700473	1.80	**31**	5.393	5.39299228	4.84
8	1.653	1.65306199	1.80	**32**	5.75	5.75000485	4.84
9	0.823	0.82296758	0.67	**33**	3.213	3.21300274	2.90
10	0.587	0.58717456	0.67	**34**	2.797	2.7969982	2.90
11	1.623	1.62301055	1.40	**35**	2.707	2.70699037	3.62
12	1.657	1.6569331	1.40	**36**	2.54	2.5400117	3.62
13	2.497	2.49700533	1.99	**37**	2.04	2.03999199	1.90
14	2.49	2.4900044	1.99	**38**	2.353	2.35299787	1.90
15	3	3.00000533	3.51	**39**	2.847	2.8469906	3.42
16	4.07	4.06999329	3.51	**40**	3.167	3.16701395	3.42
17	1.58	1.58001365	2.30	**41**	1.21	1.20997836	1.39
18	1.5	1.49995779	2.30	**42**	0.97	0.97004709	1.39
19	4.193	4.19295186	3.82	**43**	2.437	2.43700264	2.91
20	4.057	4.05703808	3.82	**44**	2.73	2.72999743	2.91
21	2.55	2.54999531	2.61	**45**	0.947	0.94703296	0.89
22	2.493	2.49302934	2.61	**46**	1.257	1.25696308	0.89
23	3.86	3.85996073	4.13	**47**	2.86	2.86000997	2.41
24	4.26	4.26003533	4.13	**48**	3.203	3.20299254	2.41
Percentage Deviation						**0.00175**	**16.833**

VI. EXPERIMENTAL RESULTS

After the development of prediction models, the models are validated with new experimental values which are not used in training set. The test data contains 14 new experimental values. For all these input values, the response of surface roughness values are predicted and compared with experimental surface roughness values and are shown in Table-X. Further, the percentage deviation is also computed and displayed in Table 10. The Fig 3 shows the difference between experimental Ra values and the values predicted by both the models for test data.

Table 10. Experimental values and Predicted values (Test Data)

Expt. No.	V(rpm)	F(mm/min)	D(mm)	NF	OL (mm)	Ra(mea)	ANN Ra	Second Order Multiple Regression Ra
1	2200	220	0.55	2	32	3.68	3.685107	2.7396
2	2200	235	0.55	2	32	3.75	3.660814	2.9631
3	2600	180	0.55	2	32	3.28	3.327078	2.1628
4	2600	180	0.75	2	32	2.87	3.004944	2.1628
5	2600	220	0.55	2	32	4.08	3.979221	2.7588
6	2600	220	0.75	2	32	3.71	6.472651	2.7588
7	2600	235	0.55	2	32	4.4	4.122594	2.9823
8	2600	235	0.75	2	32	4.11	4.091136	2.9823
9	2600	180	0.75	4	32	2.47	2.320524	2.7356
10	2600	220	0.55	4	32	3.18	3.316616	3.3316
11	2600	235	0.55	4	32	3.42	13.091	3.5551
12	2900	180	0.55	4	32	2.61	2.353685	2.2604
13	2900	180	0.75	4	32	2.48	2.515347	2.2604
14	2900	220	0.55	4	32	3.53	3.439947	2.8564
Percentage Deviation							**4.402905**	**20.2564**

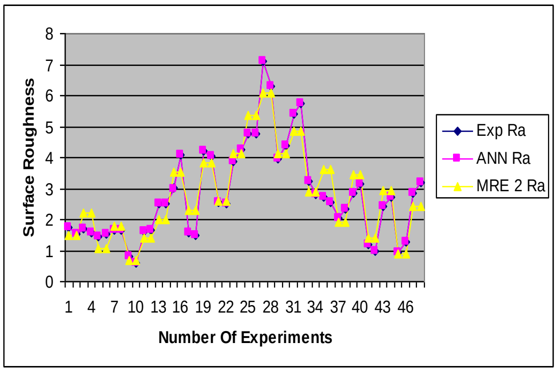

Figure 2. Experimental and predicted Ra Values (Train Data)

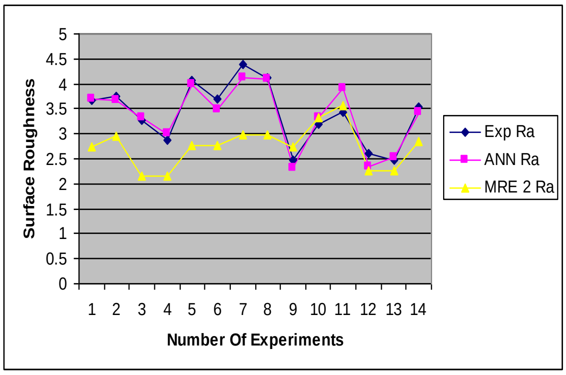

Figure 3. Experimental and Predicted Ra Values (Test Data)

VII. CONCLUSION

This paper focuses on developing a model for surface roughness prediction in CNC End-milling machine. The experiments are conducted by using Design of Experiments with mixed level. These experiments are conducted on Aluminum alloy of H30 grade using High Speed Steel tool. For the development of surface roughness prediction model, two competing modelling techniques, multiple regression and artificial neural networks, are considered.

The first order regression model is predicting the surface roughness with the independent variables of v, f, d, nf, ol and the percentage deviation of the model is 47.40% in train data and 46.70% in test data. It is observed that the first order regression model is insignificant as its F ratio from the regression analysis is less than the value from statistical tables and all the independent variables are found insignificant in the first order regression model. The second order regression model is predicting the surface roughness with independent variables in v, f, nf, vnf, vol, fol, nfol after elimination of insignificant independent variables. The percentage deviation of the model is 16.83% in train data and 17.256% in test data. In Neural Network model, the step size 0.8 and momentum 0.5 are found to be the best combination learning parameters to train the Artificial Neural Network structure. ANN model with 5-7-6-1 network structure is found as the best structure as it has lowest MSE (4.27 E-11) is obtained at 50000 epochs. ANN model is predicting the surface roughness with 0.00175% deviation in train data and 4.40% deviation in test data.

First Multiple Regression model is developed with interaction terms and without interaction terms. Then Artificial Neural Network model is developed and is compared with Multiple Regression model. The above developed models are validated with new test data. Hence, it is concluded that the Artificial Neural Network model has good capabilities of predicting high accuracy surface roughness for given input conditions, than the Multiple Regression Models.

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