

An ANFIS Model for Study of Surface Roughness for Metallic Materials on Optimized Machining Parameters

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Abstract

Machining is a process used to shape a material where the value of controlling parameters affects the quality of product. The surface roughness is one of the important quality parameters and get affected due to change in the material properties. In present study, machining process is modelled so that the surface roughness of materials can be predicted. For modelling the machining process experiments were conducted as per full factorial and Taguchi method. L9 orthogonal array has been used to design the experiments for Taguchi method. Three materials were selected for conducting the experiments: Aluminum, Copper, and Brass with a Poisson's ratio of 0.334, 0.355, 0.357 respectively. The selected input parameters for the experiments were speed, feed rate and depth of cut and output parameter was surface roughness. For the same set of input parametric values, the surface roughness obtained for each material was found different. MINITAB software is used to calculate signal to noise (S/N) ratios in order

to get optimized parametric values. The surface roughness obtained from the Taguchi method is compared with full factorial and found to be in good agreement. Further, artificial neuro fuzzy inference system (ANFIS) has been used to model the process and it is found that surface roughness values predicted are accurate up to 10% to the experimental values. It is also found that the Poisson's ratio affects the surface roughness value significantly.

Keywords:

Taguchi Method, Optimization, Design of Experiment, CNC Turning, Poisson's Ratio.

I. Introduction

Material behave differently due to its chemical composition and structure. Poisson's ratio is one of the properties by which a material can be identified. In industries turning is very commonly used subtractive process deployed to shape metallic materials. Different process parametric values are required to machine various materials into a finish product. Hard materials are difficult to machine, whereas soft materials can be machined easily [1]. So different machining parametric values were opted to machine materials to get a desired surface roughness value. The same can be modelled in the ANFIS which can further be utilized to determine the surface roughness, prior to conduct machining.

The surface roughness value of Aluminum Alloy (AA6063 T6) was determined for the optimized process parameters and found that it is an important criterion for selection

of a component as a machine part. Surface roughness is effected due to change in parameters of turning operation. The capability of a machine can be enhanced by selecting appropriate machining parameters based on their optimized values. Thus, reduces the dependencies on other finishing operations and hence makes it economical [2]. The optimization of the surface roughness, tool wear and material removal rate of Steel (AISI1060) was studied using Taguchi method. It was found that cutting speed affects the surface roughness value, depth of cut affects tool wear and feed rate affects the material removal rate significantly[3]. The effect of different turning parameters like speed, feed, and depth of cut, on Niobium alloy (C-103) was investigated. The alloy is used to manufacture aerospace component where high surface finishing is required. Poly Crystalline Diamond (PCD) coated insert tool was used for turning and found that surface roughness increases with increase in feed rate and it is highly significant for the turning operation [4]. The effect of different machining parameters of end mill, (like speed, feed, and depth of cut) on Copper alloy (C360) was investigated to obtain the optimized parameters using ANOVA and Genetic algorithm (GA). Results of ANOVA shows that feed rate has significant influence on surface roughness. It was also found that GA is an appropriate tool for optimizing the machining parameters, and the result found are within the acceptable limits of 10% as compare with the confirmation experiments [5]. Studies shows that machining parametric values effects the surface roughness of materials differently. In our study

we have considered Aluminum, Copper, and Brass so that the effect of machining parameter on surface roughness value can be investigated.

Taguchi Method is used to optimize the parametric values of manufacturing process. It is based on planning, conducting, and evaluating the matrix to determine the most desirable control factors by maximizing the signal to noise ratio (S/N). In static Taguchi approach, the optimization is achieved by using three S/N ratios: smaller the better, larger the better and nominal the best. All the three signal ratios are as follows,

$$\text{S/N ratio, smaller the better, } \eta_s = -10 \log_{10} \frac{1}{n} \sum_{i=1}^n y_i^2$$

$$\text{S/N ratio, larger the better, } \eta_s = -10 \log_{10} \frac{1}{n} \sum_{i=1}^n \frac{1}{y_i^2}$$

$$\text{S/N ratio, nominal the best, } \eta_s = -10 \log_{10} \sigma^2$$

Where, ‘n’ is the number of experiments conducted, ‘y’ is the mean value of outputs, ‘y_i’ is the ith observed value of the output and ‘σ’ is the standard deviations.

The orthogonal experiment design and Taguchi approach was used to reduce the variation in the input parameters and improve the quality of the product economically [6]. It was also found that cutting speed affects the surface roughness value, depth of cut affects tool wear and feed rate affects the material removal rate significantly [3]. Taguchi method grey-relational-analysis (GRA) was used to minimize surface roughness and cutting force. Taguchi L27 array was used for designing the experiment

and ANOVA was applied to know the significance of the input parameters. It was found that the interaction between the input parameters do not have significant effect on the output parameters and the most significant input parameters effecting the machining output parameters are in order of feed rate, cutting depth, cutting speed and then chrome ratio [7].

Taguchi method was used to optimize the parameters of electric discharge machining process for high strength and temperature resistance (HSTR) material. L9 orthogonal array was used to design the experiment and trials were performed accordingly. The results of trials were analyzed further using MINITAB software to obtain the optimized values of input parameters in order to get the higher material removal rate and lower surface roughness value [8]. The effect of cutting parameters (Cutting speed, feed rate, Depth of cut, and tool path) of pocket machining on the surface roughness was investigated. Taguchi L27 orthogonal array was used to design the experiment. Trials were performed on three axes vertical milling machine. MINITAB software was used to calculate the Taguchi function (Smaller is Better) and found that tool path does not have significant effect on surface roughness. It was also found that optimized levels of input parameter give up to 95% accurate results [9].

Once optimization of process is done, the system can be modelled so that the results can be predicted. One of the methods is adaptive neuro-fuzzy inference system (ANFIS). ANFIS was used to estimate the surface roughness value and tool profile in a machining process. The system was modelled using response surface methodology

(RSM) and further optimized by using composite desirability approach (CDA). It was found that the result predicted using ANFIS is closer to the experimental value than the results obtained by RSM. The ANOVA was used to find the factors affecting the surface roughness, temperature and cutting force. The cutting speed influences cutting force and temperature whereas feed rate influences surface roughness [10]. ANFIS based PSO (partial swarm optimization) was used to predict surface roughness characteristics and cutting zone temperature values for turning of AISI304 stainless steel. ANFIS involves five layers which are, fuzzification layer, product layer, normalized layer, rule layer, and output layer. Gaussian membership function is used for training process of ANFIS. It was found that the ability to prognosticate the outputs using ANFIS based PSO is very efficient and powerful tool for manufacturing industries [11]. The milling parametric values: spindle speed, feed rate, and depth of cut were studied to predict surface roughness value of brass through ANFIS model and was found in good agreement with the measured values with average error of 2.75% [12]. A model was developed to estimate the surface roughness, tool wear ratio, and metal removal rate of micro-machining process using ANFIS. The model was further used to find all three outputs with respect to four input parameters (Cutting speed, feed rate, depth of cut, average gray level) and found that the ANFIS model can be used to prognosticate the experimental data [13]. A relationship was established between input parameters (feed, DoC, speed) and output parameters (surface roughness and cutting force) for a Cryogenically treated stainless steel insert with other inserts by using

ANFIS tool and found that the predicted results are very close to the experimental data [14]. The effect of different turning parameters speed, feed, and depth of cut on material removal rate and surface roughness of stainless steel 202 was studied and found that ANFIS model predicts the value of output parameters with an accuracy more than 98 percent [15].

In this paper a method has been developed to model a process using ANFIS to determine the surface roughness value for three different materials (Aluminum, Copper, Brass). The Poisson's ratio are 0.334, 0.355, 0.357 for Aluminum, Copper, and Brass respectively [16]. The change in the Poisson's ratio was to observe the response of machining parametric values and to estimate the variation in surface roughness value. For modelling the machining process experiments were conducted as per full factorial and Taguchi method. L9 orthogonal array has been used to design the experiments for Taguchi method the details are discussed in the following sections.

II. Experimental Procedure

For investigating the effect of Poisson's ratio on surface roughness, we have considered three different materials (Aluminum, Copper, Brass). Some of the machining process parameters are important and it significantly influences the surface roughness [1, 8]. The process parameters (input) which were selected for investigation are spindle speed, depth of cut and feed rate. We have considered three different levels

for each input parameter for conducting the experiment as tabulated in Table 1 [4, 7, 8, 10]. Selected specimen was having diameter 12mm and length 70mm in order to suffice the machining and surface roughness requirement.

Table 1: Input Process Parameter with levels

Symbol	Parameters	Unit	Levels		
			1	2	3
X ₁	Spindle Speed	Rpm	1500	2000	2500
X ₂	Feed Rate	mm/min	70	80	90
X ₃	Depth of Cut	Mm	0.25	0.5	0.75

The experiments were performed for two different series. In first series we have used Taguchi method, where L9 orthogonal array were used for conducting the experiment. In this method we have conducted nine experiments in three repetition for each material resulted in to eighty one (9X3X3) experiments. In the second series of experiments full factorial was used, where 27 experiments in three repetition for each material resulted into 243(3³ X 3 X 3) experiments. Thus, total number of experiments (turning) were finalized. The experiments (i.e., turning operation using CNC turning machine-MTAB) were performed and surface roughness (R_a) value were measured using surface roughness testing machine (Digital Surface Roughness Tester of Model: SJ-210) as shown in Figure 1. Based on these values the signal to noise ratio (SNR) were determined. The SNR is a function of mean of sum of square of average roughness value (R_a), where $SNR = -10 \log_{10} \left(\frac{1}{n} \sum_{i=1}^n R_a^2 \right)$.



Fig.1: Surface Roughness Testing Machine (Model: SJ-210)

Table 2 (a), (b), and (c) are the experimental results for Taguchi Method and Table 3 (a), (b), and (c) are for full factorial, where for input parameters (spindle speed, feed rate, and depth of cut), the output parameter (surface roughness) was determined for three trials. Mean for these trial were determined and the SNR were calculated.

Table 2(a) Taguchi data with trail variation (Aluminum)

S No	Spindle Speed (rpm)	Feed Rate (mm/min)	Depth of Cut (mm)	Mean (R_a)	Ra (Trail 1)	Ra (Trail 2)	Ra (Trail 3)	SNR
1	1500	70	0.25	0.40	0.39	0.40	0.41	7.96
2	1500	80	0.5	0.70	0.70	0.69	0.72	3.06
3	1500	90	0.75	0.59	0.58	0.59	0.59	4.63
4	2000	70	0.5	2.35	2.41	2.20	2.44	-7.43
5	2000	80	0.75	0.55	0.57	0.53	0.56	5.14
6	2000	90	0.25	0.40	0.40	0.42	0.38	7.95
7	2500	70	0.75	2.25	2.26	2.24	2.25	-7.04
8	2500	80	0.25	1.26	1.25	1.26	1.28	-2.03
9	2500	90	0.5	1.44	1.44	1.42	1.46	-3.17

Table 2(b) Taguchi data with trail variation (Copper)

S No	Spindle Speed (rpm)	Feed Rate (mm/min)	Depth of Cut (mm)	Mean (R_a)	Ra (Trail 1)	Ra (Trail 2)	Ra (Trail 3)	SNR
1	1500	70	0.25	0.85	0.90	0.78	0.88	1.36
2	1500	80	0.5	0.82	0.82	0.78	0.86	1.72

3	1500	90	0.75	2.99	3.46	2.70	2.80	-9.56
4	2000	70	0.5	0.75	0.59	0.68	0.98	2.29
5	2000	80	0.75	1.83	1.70	1.89	1.90	-5.26
6	2000	90	0.25	1.06	1.00	1.09	1.09	-0.51
7	2500	70	0.75	0.92	1.20	0.85	0.72	0.49
8	2500	80	0.25	1.40	1.40	1.39	1.41	-2.92
9	2500	90	0.5	1.93	1.90	2.10	1.80	-5.74

Table 2(c) Taguchi data with trail variation (Brass)

S No	Spindle Speed (rpm)	Feed Rate (mm/min)	Depth of Cut (mm)	Mean (R_a)	Ra (Trail 1)	Ra (Trail 2)	Ra (Trail 3)	SNR
1	1500	70	0.25	1.63	1.65	1.69	1.54	-4.23
2	1500	80	0.5	1.67	1.60	1.75	1.67	-4.48
3	1500	90	0.75	2.24	2.20	2.55	1.98	-7.07
4	2000	70	0.5	1.57	1.40	1.73	1.58	-3.95
5	2000	80	0.75	1.19	1.00	1.30	1.10	-1.14
6	2000	90	0.25	1.51	1.47	1.48	1.59	-3.60
7	2500	70	0.75	2.39	2.70	2.38	2.60	-8.18
8	2500	80	0.25	2.11	2.00	2.10	2.23	-6.49
9	2500	90	0.5	2.93	2.80	3.10	2.90	-9.36

Table 3(a): Full factorial data with three trails for Aluminum

S No	Spindle Speed (rpm)	Feed Rate (mm/min)	Depth of Cut (mm)	Mean (R_a)	Ra (Trail 1)	Ra (Trail 2)	Ra (Trail 3)	SNR
1	2000	80	0.5	0.76	0.73	0.74	0.8	2.41
2	2000	80	0.25	0.46	0.46	0.44	0.48	6.74

3	2000	80	0.75	0.55	0.57	0.53	0.56	5.14
4	2000	70	0.5	2.35	2.41	2.2	2.44	-7.43
5	2000	70	0.25	0.41	0.41	0.4	0.43	7.67
6	2000	70	0.75	0.62	0.63	0.6	0.64	4.1
7	2000	90	0.5	0.41	0.41	0.4	0.42	7.74
8	2000	90	0.25	0.4	0.4	0.42	0.38	7.95
9	2000	90	0.75	0.52	0.54	0.52	0.49	5.73
10	1500	80	0.5	0.7	0.7	0.69	0.72	3.06
11	1500	80	0.25	0.54	0.53	0.55	0.54	5.35
12	1500	80	0.75	0.45	0.46	0.45	0.44	6.93
13	1500	70	0.5	0.73	0.74	0.73	0.72	2.73
14	1500	70	0.25	0.4	0.39	0.4	0.41	7.96
15	1500	70	0.75	0.38	0.37	0.38	0.39	8.4
16	1500	90	0.5	0.51	0.5	0.51	0.52	5.85
17	1500	90	0.25	0.46	0.45	0.46	0.46	6.81
18	1500	90	0.75	0.59	0.58	0.59	0.59	4.63
19	2500	80	0.5	1.55	1.58	1.56	1.5	-3.79
20	2500	80	0.25	1.26	1.25	1.26	1.28	-2.03
21	2500	80	0.75	1.75	1.77	1.79	1.7	-4.88
22	2500	70	0.5	1.82	1.85	1.79	1.82	-5.2
23	2500	70	0.25	0.94	0.94	0.92	0.96	0.54
24	2500	70	0.75	2.25	2.26	2.24	2.25	-7.04
25	2500	90	0.5	1.44	1.44	1.42	1.46	-3.17
26	2500	90	0.25	1.69	1.69	1.68	1.7	-4.56
27	2500	90	0.75	0.43	0.42	0.43	0.44	7.33

Table 3(b): Full factorial data with three trails for Copper

S No	Spindle Speed (rpm)	Feed Rate	Depth of Cut (mm)	Mean (R_a)	Ra (Trail 1)	Ra (Trail 2)	Ra (Trail 3)	SNR
1	2000	80	0.5	1.79	1.78	1.8	1.79	-5.06
2	2000	80	0.25	1.82	1.8	1.84	1.82	-5.2
3	2000	80	0.75	1.83	1.7	1.89	1.9	-5.26
4	2000	70	0.5	0.75	0.59	0.68	0.98	2.29
5	2000	70	0.25	1.21	1.21	1.19	1.23	-1.66
6	2000	70	0.75	0.75	0.95	0.6	0.69	2.37
7	2000	90	0.5	1.26	1	1.46	1.32	-2.11
8	2000	90	0.25	1.06	1	1.09	1.09	-0.51
9	2000	90	0.75	1.39	1.38	1.38	1.41	-2.86
10	1500	80	0.5	0.82	0.82	0.78	0.86	1.72
11	1500	80	0.25	2.11	2.14	2.12	2.13	-6.57
12	1500	80	0.75	0.85	0.9	0.7	0.95	1.34
13	1500	70	0.5	2.01	1.7	2.4	1.93	-6.15
14	1500	70	0.25	0.85	0.9	0.78	0.88	1.36
15	1500	70	0.75	0.83	0.82	0.82	0.85	1.62
16	1500	90	0.5	2.67	2.67	2.67	2.66	-8.52
17	1500	90	0.25	1.04	1	1.04	1.09	-0.37
18	1500	90	0.75	2.99	3.46	2.7	2.8	-9.56
19	2500	80	0.5	5.07	5	5	5.2	-14.1
20	2500	80	0.25	1.4	1.4	1.39	1.41	-2.92
21	2500	80	0.75	0.61	0.6	0.62	0.61	4.29
22	2500	70	0.5	1.39	1.41	1.38	1.39	-2.88
23	2500	70	0.25	3.25	3	3.05	3.7	-10.28
24	2500	70	0.75	0.92	1.2	0.85	0.72	0.49
25	2500	90	0.5	1.93	1.9	2.1	1.8	-5.74
26	2500	90	0.25	12.29	12.29	12.27	12.28	-21.78
27	2500	90	0.75	0.68	0.65	0.69	0.7	3.35

Table 3(c): Full factorial data with three trails for Brass

S No	Spindle Speed (rpm)	Feed Rate	Depth of Cut (mm)	Mean (R_a)	R_a (Trail 1)	R_a (Trail 2)	R_a (Trail 3)	SNR
1	2000	80	0.5	1.46	1.45	1.47	1.46	-3.29
2	2000	80	0.25	1.36	1.3	1.32	1.46	-2.68
3	2000	80	0.75	1.19	1	1.3	1.1	-1.14
4	2000	70	0.5	1.57	1.4	1.73	1.58	-3.95
5	2000	70	0.25	1.42	1.42	1.4	1.44	-3.05
6	2000	70	0.75	1.53	1.42	1.4	1.44	-3.05
7	2000	90	0.5	1.54	1.55	1.48	1.6	-3.77
8	2000	90	0.25	1.51	1.47	1.48	1.59	-3.6
9	2000	90	0.75	1.49	1.5	1.49	1.48	-3.46
10	1500	80	0.5	1.67	1.6	1.75	1.67	-4.48
11	1500	80	0.25	1.62	1.53	1.68	1.65	-4.2
12	1500	80	0.75	1.69	1.69	1.57	1.6	-4.19
13	1500	70	0.5	1.66	1.6	1.75	1.64	-4.43
14	1500	70	0.25	1.63	1.65	1.69	1.54	-4.23
15	1500	70	0.75	1.58	1.57	1.59	1.58	-3.97
16	1500	90	0.5	1.8	1.8	1.81	1.82	-5.15
17	1500	90	0.25	1.97	1.85	2.1	1.95	-5.89
18	1500	90	0.75	2.24	2.2	2.55	1.98	-7.07
19	2500	80	0.5	1.87	1.9	1.8	1.9	-5.42
20	2500	80	0.25	2.11	2	2.1	2.23	-6.49
21	2500	80	0.75	2.26	2.24	2.28	2.26	-7.08
22	2500	70	0.5	2.16	2.16	2.16	2.16	-6.69
23	2500	70	0.25	2.56	2.7	2.38	2.6	-8.18
24	2500	70	0.75	2.39	2.7	2.38	2.6	-8.18
25	2500	90	0.5	2.93	2.8	3.1	2.9	-9.36
26	2500	90	0.25	2.45	2.45	2.45	2.45	-7.78

27	2500	90	0.75	2.52	2.6	2.5	2.45	-8.02
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Table 4 (a): Response Table for Signal to Noise Ratios (*smaller is better*) for Aluminum

Level	A	B	C
1	5.21	-2.17	4.63
2	1.89	2.05	-2.51
3	-4.08	3.14	0.91
Delta	9.30	5.31	7.14
Rank	1	3	2

Table 4 (b): Response Table for Signal to Noise Ratios (*smaller is better*) for Copper

Level	A	B	C
1	-2.16	1.38	-0.69
2	-1.16	-2.16	-0.58
3	-2.73	-5.27	-4.78
Delta	1.56	6.65	4.20
Rank	3	1	2

Table 4 (c): Response Table for Signal to Noise Ratios (*smaller is better*) for Brass

Level	A	B	C
1	-5.26	-5.45	-4.78
2	-2.90	-4.04	-5.93
3	-8.01	-6.68	-5.46
Delta	5.11	2.64	1.15
Rank	1	2	3

The optimized value of process parameters to get minimum surface roughness values for materials with different Poisson's ratio are tabulated in Table 3 and Table 4. The optimum parameter levels obtained using Taguchi method were very close to the experimental values and is evident in Table 2 and therefore the Taguchi parameter design gives accurate results with lesser number of experiments.

Optimized surface roughness value for materials with different Poisson's ratio were further plotted as shown in the Figure 8 for useful analysis.

The optimized value of process parameters to get minimum surface roughness values for materials with different Poisson's ratio are tabulated in Table 4. The optimum parameter levels obtained using Taguchi method were very close to the experimental values and is evident in Table 2 and therefore the Taguchi parameter design gives accurate results with lesser number of experiments.

Optimized surface roughness value for materials with different Poisson's ratio were further plotted as shown in the Figure 2 for useful analysis.

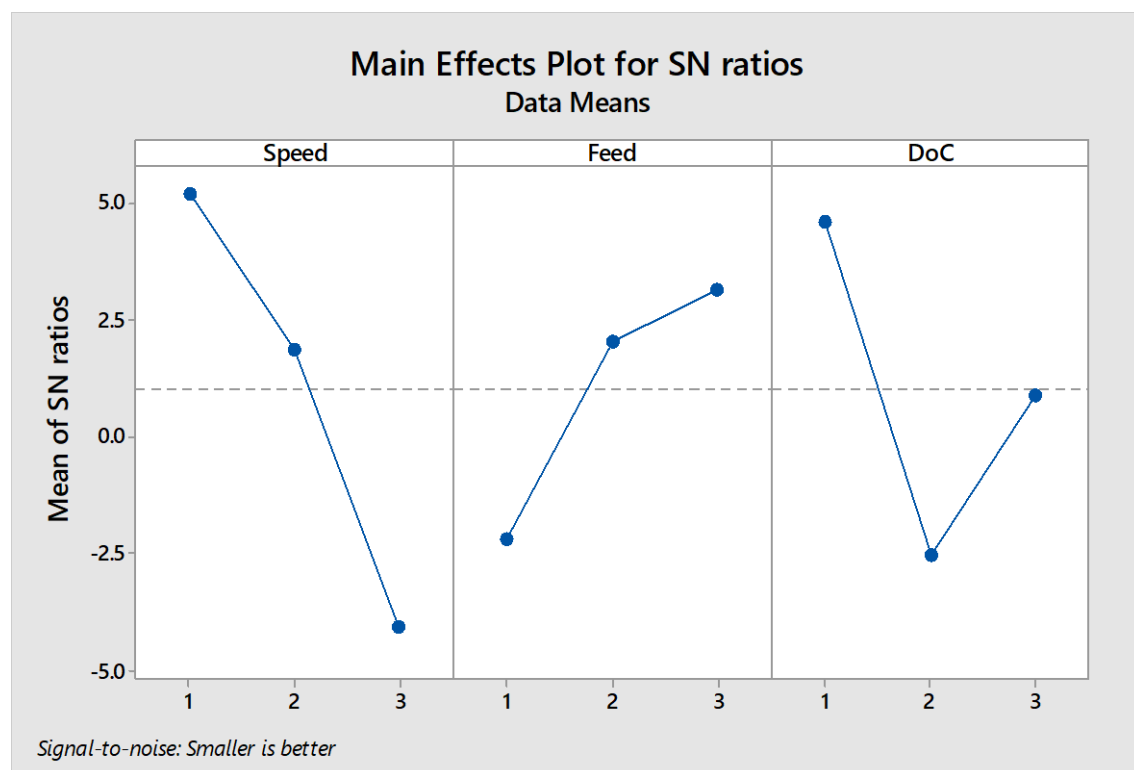


Fig. 2a. Plots for Mean of SN Ratios (Aluminum)

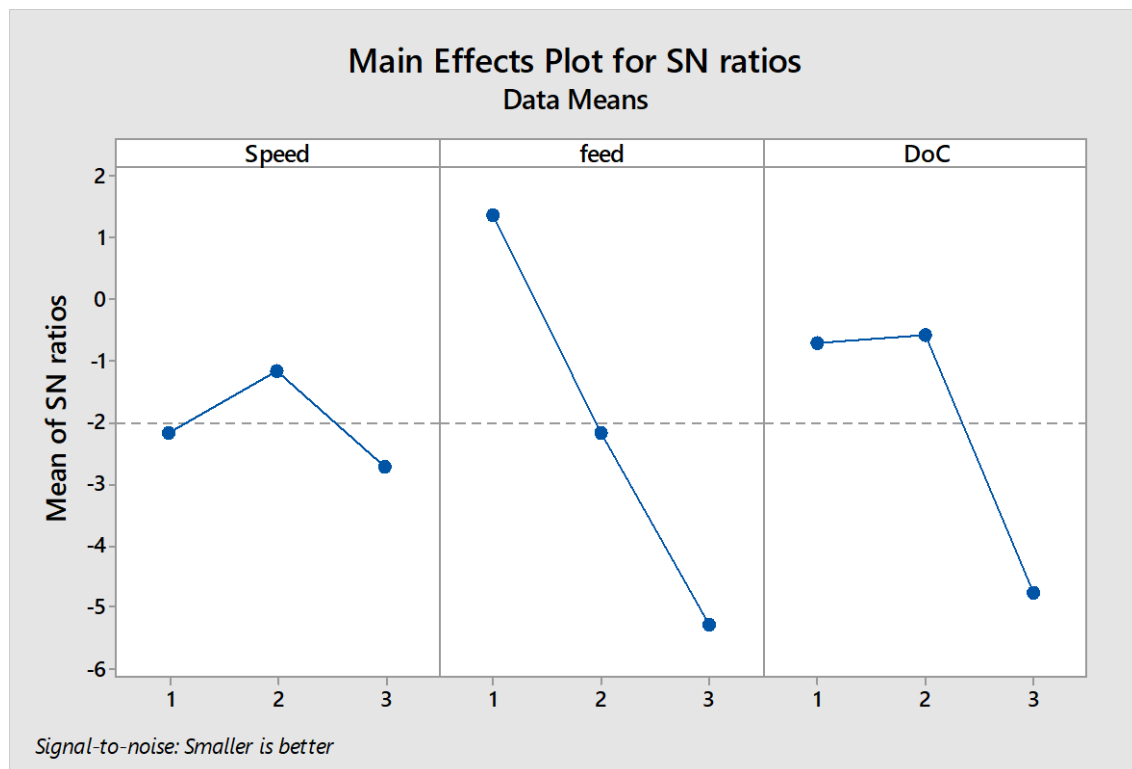


Fig. 2b. Plots for Mean of SN Ratios (Copper)

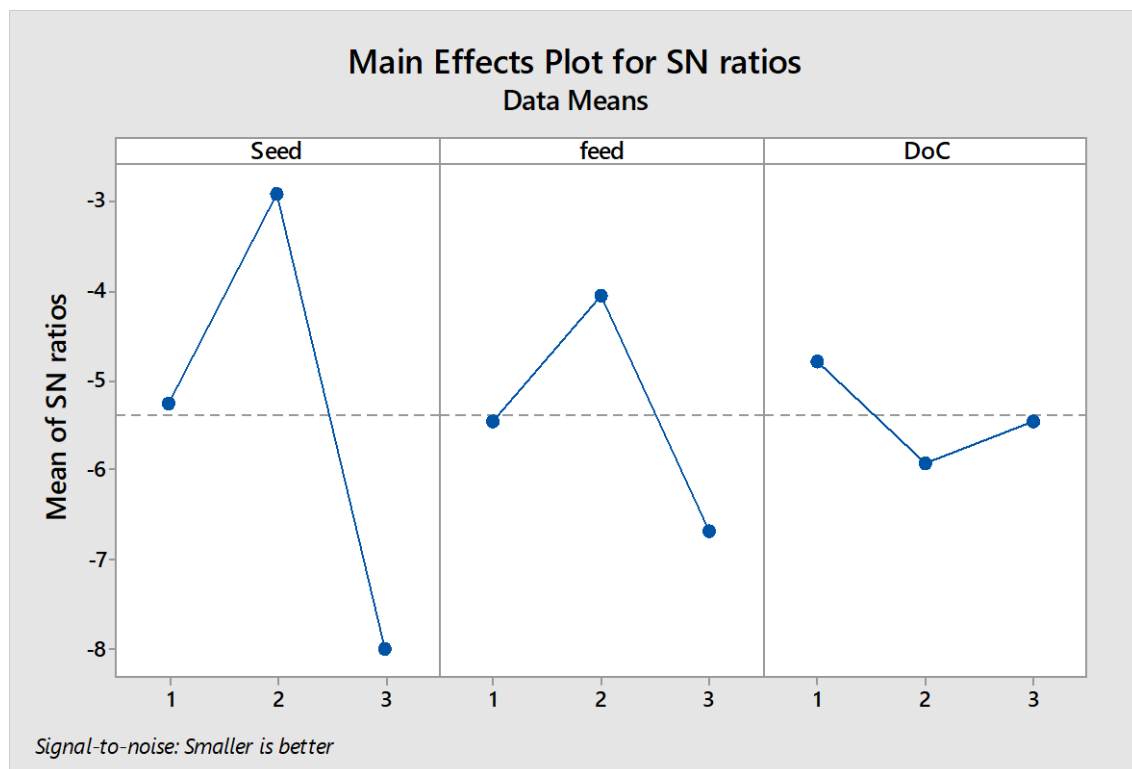


Fig. 2c. Plots for Mean of SN Ratios (Brass)

III. Adaptive Neuro-Fuzzy Interference System

Adaptive Neuro-Fuzzy Interference System (ANFIS) was used to model the machining parameters to predict surface roughness. The experimental data as obtained from the full-factorial method is used as an input file for developing Fuzzy Interference System (FIS). In this FIS system we have incorporated hybrid optimization method where 50 epochs within a tolerance of 0.00001 was used to generate FIS. The input membership function type was trapezoidal and output membership function type was linear. The FIS output is utilized to develop ANFIS model, which is further tested and verified with the experimental data (full-factorial random sample). The ANFIS model and

model structure generated is as shown in the figure 3 and figure 4 respectively is for Aluminum. The surface plot was generated based on the output from the ANFIS to observe the characteristics with variation in the input parametric values. For Aluminum number of fuzzy rules were 27 and the training completed at epoch 2 with training error of 0.00031373. Once training is over testing was performed. The thirty percent of the experimental data was used for the purpose. It was found that average testing error was 0.00014932. The plot of surface roughness against feed rate and spindle speed for aluminum is as shown in the figure 5a. The plot of surface roughness against depth of cut and spindle speed for aluminum is as shown in the figure 5b. Modelling process was further prepared for copper and brass.

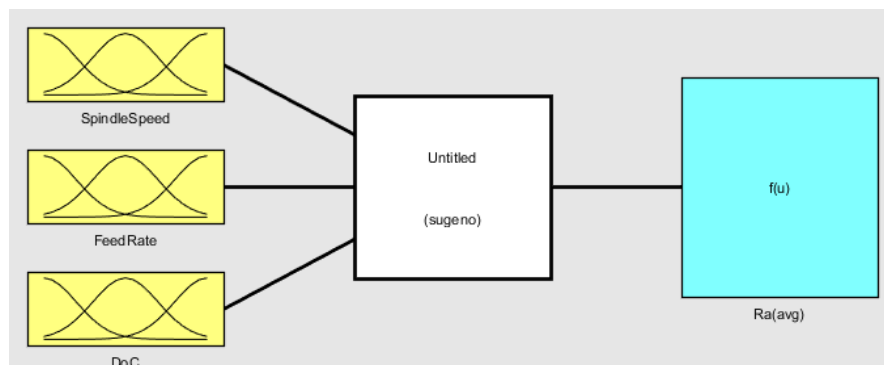


Fig. 3. ANFIS Model

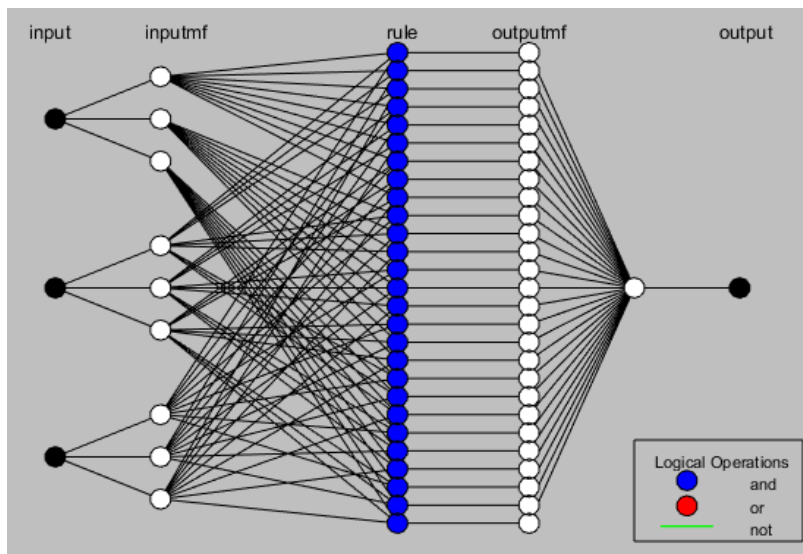


Fig. 4. Structure of ANFIS Model

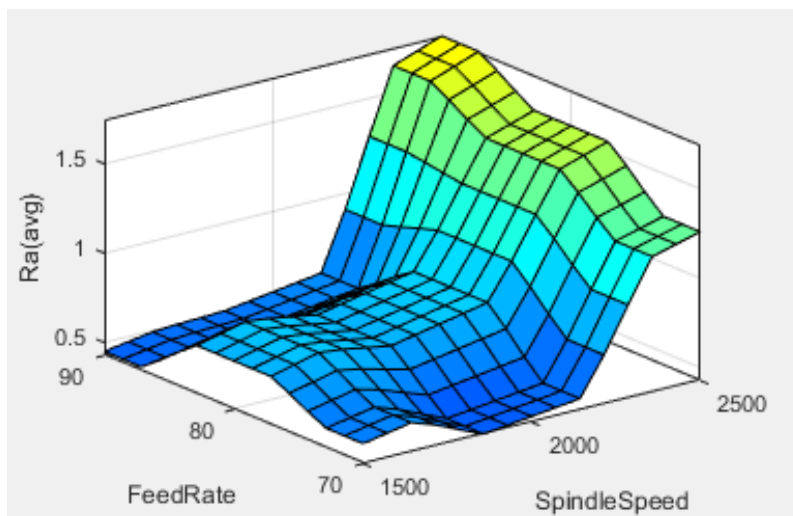


Fig. 5a. Plot of surface roughness with change in feed rate and spindle speed for aluminum

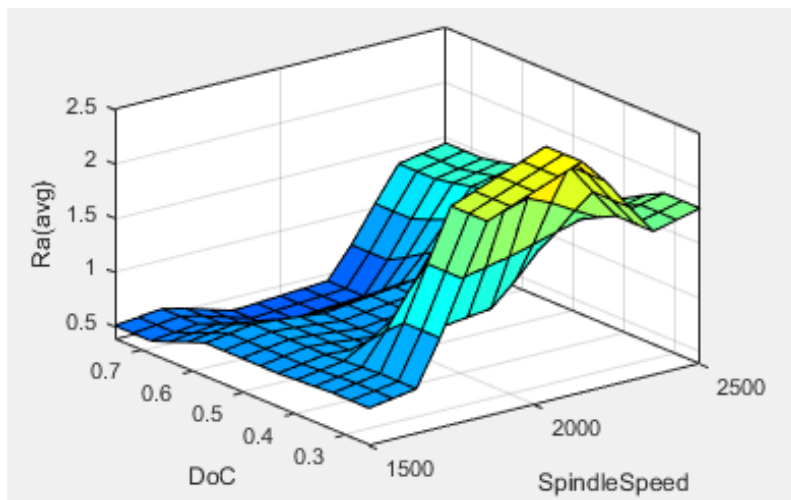


Fig. 5b. Plot of surface roughness with change in depth of cut (DoC) and spindle speed for aluminum

For copper the training completed at epoch 2 with training error of 0.00069659 and average testing error is 0.00025251. The plot of surface roughness against feed rate and spindle speed for copper is as shown in the figure 6a. The plot of surface roughness against depth of cut and spindle speed for copper is as shown in the figure 6b.

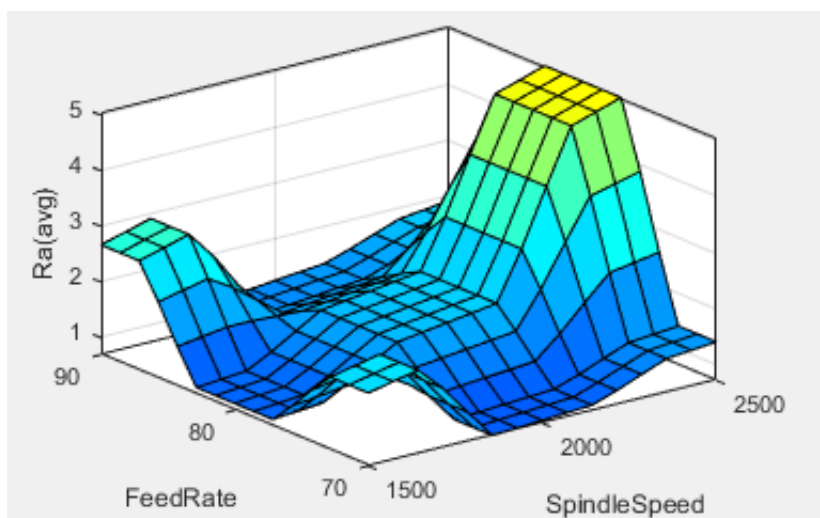


Fig. 6a. Plot of surface roughness with change in feed rate and spindle speed for copper

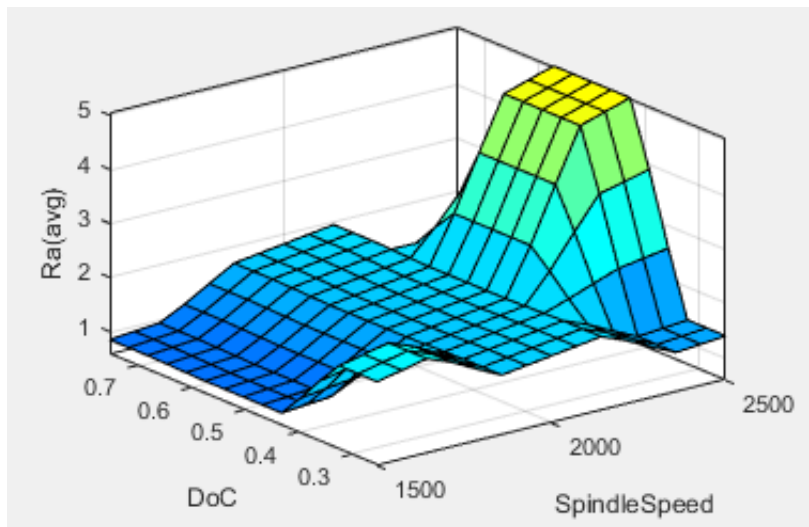


Fig. 6b. Plot of surface roughness with change in depth of cut (DoC) and spindle speed for copper

In case of brass the training completed at epoch 2 with training error of 0.0006061 and average testing error was 0.00052634. The plot of surface roughness against feed rate and spindle speed for brass is as shown in the figure 7a. The plot of surface roughness against depth of cut and spindle speed for brass is as shown in the figure 7b.

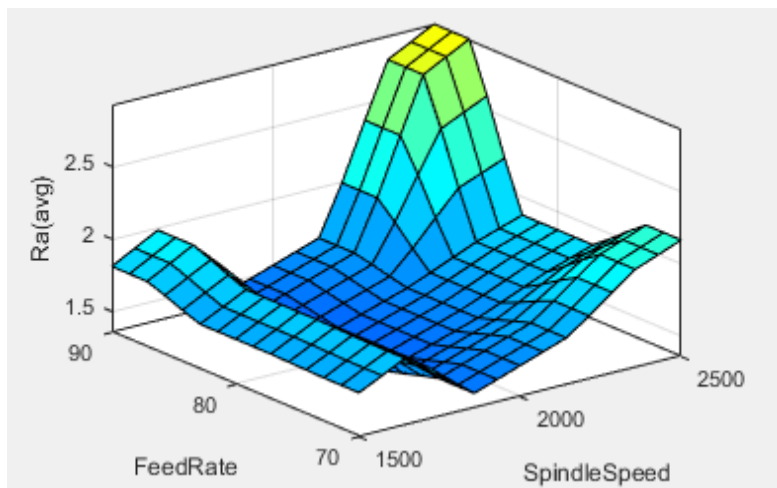


Fig. 7a. Plot of surface roughness with change in feed rate and spindle speed for brass

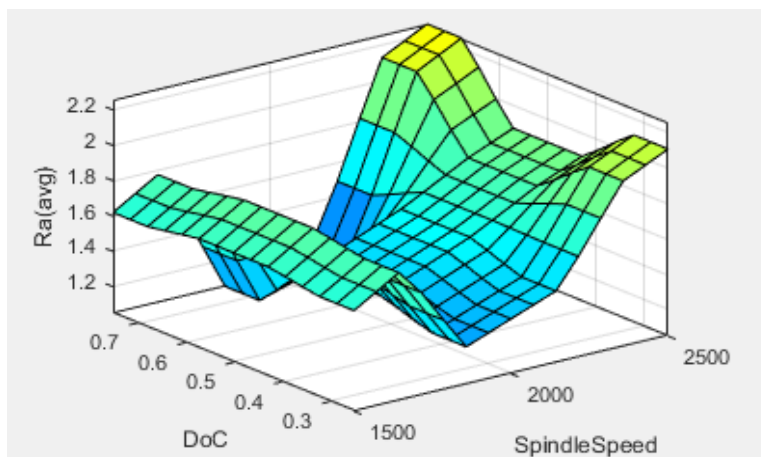


Fig. 7b. Plot of surface roughness with change in depth of cut (DoC) and spindle speed for brass

IV. Result and Discussion

A series of experiments were conducted for full factorial data set to determine the

surface roughness for three different materials as tabulated in the table 3a, 3b, and 3c. The surface roughness (Ra) value for Aluminum having maximum value of 2.41, minimum value of 0.37, mean value of 0.903, and median value of 0.58. The surface roughness (Ra) value for Copper having maximum value of 12.29, minimum value of 0.61, mean value of 1.98, and median value of 1.26. The surface roughness (Ra) value for Brass having maximum value of 2.93, minimum value of 1.19, mean value of 1.85, and median value of 1.66. For copper the maximum surface roughness was 12.29 (reflects a poor surface finish) may be due to higher tool temperature (as coolant was not used), high spindle speed and high feed rate. If we exclude the combination of parametric level values for which Ra is 12.29, then the mean value happens to be 1.59. Thus we say that with increase in passion ratio the surface roughness increases.

The machining parameters were optimized using Taguchi method to reduce the number of experiments to determine the surface roughness values. Thus, a new set of experimental data were determined and the surface roughness value for the three different materials were tabulated in table 2a, 2b, and 2c. The surface roughness (Ra) value for Aluminum, having maximum value of 1.82, minimum value of 0.38, mean value of 0.93, and median value of 0.54. The surface roughness (Ra) value for Copper, having maximum value of 2.99, minimum value of 0.75, mean value of 1.39, and median value of 1.06. The surface roughness (Ra) value for Brass, having maximum value of 2.93, minimum value of 1.19, mean value of 1.92, and median value of 1.67. The maximum and minimum value of surface roughness in case of Taguchi method

has minimum variation and is close to mean value, whereas in case of full factorial method the variation is noticeable. It has been observed that in case of Brass the maximum, minimum, mean and median value of surface roughness remain consistent with full factorial and Taguchi method.

For validating the data obtained for L9 orthogonal array (Taguchi) and Full factorial we have developed ANFIS model for the three-material using MATLAB. Based on the system model developed we then determined the surface roughness (Ra) values for all the three models as shown in figure 8. The percentage error in the experimental and the ANFIS model data for Aluminum are, having maximum value of 0.81%, minimum value of -0.73%, mean value of 0.01%, and median value of 0.00% (Zero percentage). The percentage error in the experimental and the ANFIS model data for Copper are, having maximum value of 0.17%, minimum value of -0.16%, mean value of 0.01%, and median value of 0.00% (Zero percentage). The percentage error in the experimental and the ANFIS model data for Brass are, having maximum value, minimum value, mean value, and median value of 0.00% (Zero percentage). It is observed from the figure 8 that with increase in spindle speed value and feed rate the increment in the surface roughness value is evident, also with increase in Poisson's ratio value the surface roughness value increases.

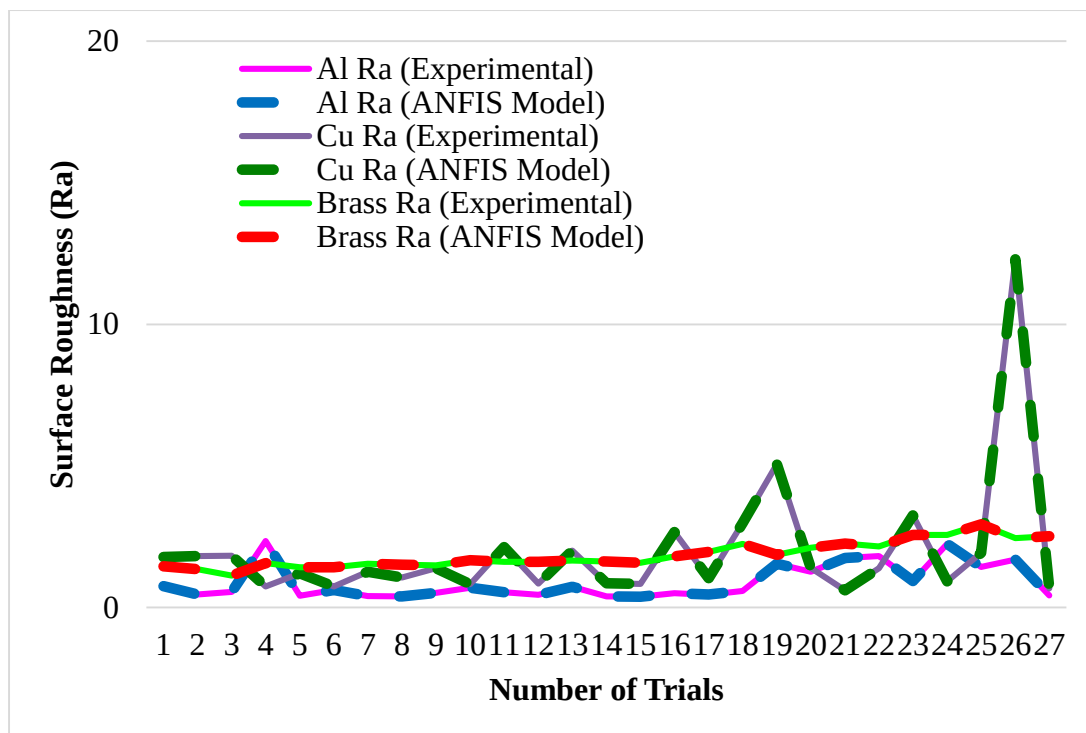


Fig. 8. Plot of surface roughness for number of trails of experimental data and data obtained from ANFIS Model.

V. Conclusion

In this paper surface roughness of the machined specimen of three different materials was studied, when the machining parameter was varied. Taguchi method was implemented to reduce the number of machining operation, based on the optimized machining parameters. The Taguchi results and found to have good correlation with that of full factorial method. Further, individual ANFIS model was developed in MATLAB to validate the results of Taguchi method for each material.

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