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Parametric Study of CNC Turning Process Parameters for Surface Roughness using ANN and GA

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Abstract - *Now a day's achieving a good Surface Finish is the main focus in the metal cutting industry during turning processes. The present work is to investigate the effect of speed, cutting speed (feed) and depth of cut in computer numeric control i.e. CNC machine. The experimental results will establish connection between speeds, feed and cutting speed and the surface roughness. Food industries use the stainless steel grade 304. So the material that will be used is SS304 and the application of it will be on shaft used for fruit pulper machine. The experimental results will be then collected and analyzed with the help of the ANN and GA. ANN and Genetic Algorithm is to be performed to find the significance of the cutting parameters on the Surface roughness. The optimal cutting parameter settings will be determined, as well as level of importance of the cutting parameters. Also ANN (Artificial Neural Networking) and GA (Genetic Algorithm) will be used to create relation between input data sets and predict the surface finish output for the given sets of inputs. So that input parameters can be decided for the requirements of different surface finishes directly. Mat lab software package will be used to perform ANN and GA analysis on the data sets.*

Keywords: *Stainless Steel 304 material, Surface Roughness Tester, CNC Machine, ANN, GA, Mat Lab.*

1. INTRODUCTION

The surface quality is an important parameter to evaluate the productivity of machine tools as well as machined components. Hence, achieving the desired surface quality is of great importance for the functional behavior of mechanical parts. Surface roughness is used as the critical quality indicator for the machined surfaces and it affects the several properties such as wear resistance, fatigue strength, coefficient of friction, lubrication, heat transmission, wear rate and corrosion resistance of the

Machined parts today every manufacturing industry, special attention is given to dimensional accuracy and surface finish. Thus, measuring and characterizing the surface finish can be considered as a predictor for the machining performance. The mechanism behind the formation of surface roughness is very dynamic, complicated, and process dependent [1]. Surface roughness in turning process has been found to be influenced in varying amounts by a number of factors such as cutting parameters, cutting fluid, and work piece hardness [2]. Many investigations on surface roughness of various metallic materials have been carried out but very few on soft materials such as polymers. The polymers require machining operations at the final assembly stage in order to get the finished components, even though they are produced as near net shapes [3]. Nevertheless, the knowledge regarding the machining of polyamides is limited. Hence the machining of polymers often presents challenges to engineers in terms of close tolerances, their unusual geometry, and softness, which means that it behaves differently as compared with conventional metal cutting [4]. Among various types of polymers, the polyamides have attracted a great deal of interest over the last few years. Modeling the correlation between cutting parameters and process parameters in machining of polyamides is of prime interest. Besides traditional empirical modeling using regression analysis (RA), the artificial neural network (ANN) based modeling is increasingly becoming popular. To ensure the quality of machining products, and to reduce the machining costs and increase the machining effectiveness, it is very important to select the optimal machining parameters [5]. The selection of cutting tool and process parameters is very much essential in machining of polymers [6]. In machining practice, most of the time the optimal cutting conditions are determined using Taguchi method and by coupling empirical models based on RA and ANNs with different optimization algorithms. This study was inspired by the very limited work on the application of ANNs in modeling the relationship between cutting parameters and surface roughness during turning of polyamide, as well as determining the optimal cutting conditions for minimizing surface roughness. The surface roughness model was developed in terms of cutting speed, feed rate, depth of cut, and tool nose radius using the data from the turning experiments conducted according to Taguchi's L27 orthogonal array (OA). The optimal cutting parameter settings were determined by applying the harmony search algorithm (HSA) [7] to the developed mathematical model of surface roughness based on ANN.

2. EXPERIMENTAL WORK

In the present work SS304was machined on Conventional lathe by using a Tungsten Carbide (Ti C) tool the chemical composition of SS304is given in Table-1. Full factorial design L27 (3^3) orthogonal array was chosen for the experimental design. Experiments were conducted by varying the cutting parameters and the average surface roughness values (Ra) were measured by using Mituto211 Surf test with a sampling length of 5 mm. The considered cutting parameters and their level are shown in Table-2.

Component	Wt. %
C	Max 0.08
Cr	18 - 20
Fe	66.345 - 74
Mn	Max 2
Ni	8 - 10.5
P	Max 0.045
S	Max 0.03
Si	Max 1

Table-1: Chemical Composition of SS304

In the study, the average surface roughness (*Ra*) was considered. The machined surface was measured around the circumference of the work piece using the surface profilometer Surf test Mitutoyo SJ-210-P. To develop mathematical model based on ANN that relates the cutting parameters and average surface roughness (*Ra*), a plan of experiment is needed. The classical design of experiment (DOE) is sometimes too complex, time consuming and not easy to use. Hence, in the present investigation, the Full factorial design DOE was applied. Four cutting parameters, namely, cutting speed (*s*), feed rate (*f*), and depth of cut (*d*), were considered. The cutting parameter ranges were selected based on preliminary investigations and previous
Researches by the cutting parameters were arranged in standard full factorial design L27 Orthogonal Array.

Parameter	Unit	Levels		
		1	2	3
Speed	RPM	1000	1250	1500
Feed	mm/rev	0.1	0.2	0.3
Depth of cut	mm/rev	0.1	0.2	0.3

Table-2: Cutting parameters and their levels

Machining operation is performed on the samples chosen of the standard size of 40 mm length and 32 mm diameter. Turning operation with the said input parameters in the table-2 are performed on these samples and 27 turned components are manufactured as a sample pieces to generate the data required performing ANOVA, ANN & GA. MRR can be measured by weighing the component before and after the machining operation performed, and dividing it with the number of minutes taken by the turning operation on that component. Table-3 shows all the measured MRR values for 27 experiments.

Sr.No.	SPEED	FEED	DEPTH OF CUT	MRR
1	1000	0.1	0.1	0.63
2	1000	0.2	0.1	1.26
3	1000	0.3	0.1	1.88
4	1000	0.1	0.2	1.26
5	1000	0.2	0.2	2.51
6	1000	0.3	0.2	3.77
7	1000	0.1	0.3	1.88
8	1000	0.2	0.3	3.77
9	1000	0.3	0.3	5.65
10	1250	0.1	0.1	0.79
11	1250	0.2	0.1	1.57
12	1250	0.3	0.1	2.36
13	1250	0.1	0.2	1.57
14	1250	0.2	0.2	3.14
15	1250	0.3	0.2	4.71
16	1250	0.1	0.3	2.36
17	1250	0.2	0.3	4.71
18	1250	0.3	0.3	7.07
19	1500	0.1	0.1	0.94
20	1500	0.2	0.1	1.88
21	1500	0.3	0.1	2.83
22	1500	0.1	0.2	1.88
23	1500	0.2	0.2	3.77
24	1500	0.3	0.2	5.65
25	1500	0.1	0.3	2.83
26	1500	0.2	0.3	5.65
27	1500	0.3	0.3	8.48

Table-3: Cutting parameters and their levels

2.1 Visual or Tactual

The visual or tactual is the simplest and most straight forward method of surface measurement. It is also the least accurate. Figure 2.1 below shows a commercial set of master precision reference specimens with 15 replicated surfaces, ranging in roughness from 2 to 125 in. in height. Comparators of this type are readily available with various surface finish from 2 to 1000 in. is available. The scales, used with or without a magnifier, are placed adjacent to the work piece under examination and the surfaces are compared visibly or tactually by drawing the tip of the fingernail across each at right angles to the tool marks. The fingernail touch or "feel" will be the same when both finishes are identical. In this case we have used the electronic measuring instrument and results for the all 27 components are shown in the table-4 below.

Fig: 2.1 Measurement of the Surface roughness for components

Sr. No.	Ra
1	1.552
2	3.83
3	4.905
4	2.47
5	3.564
6	2.795
7	1.272
8	3.07
9	4.091
10	1.7
11	1.415
12	3.936
13	2.216
14	2.98
15	3.783
16	2.056
17	3.276
18	4.954
19	2.021
20	1.998
21	1.2
22	2.397
23	2.738
24	2.946
25	2.559
26	1.803
27	3.425

Table-4: Experimental Ra values

3. ANALYSIS OF VARIANCE (ANOVA) S/N ANALYSIS

The S/N ratio is a concurrent quality metric linked to the loss function (Barker, 1990). By maximizing the S/N ratio, the loss associated can be minimized. The S/N ratio determines the most robust set of operating conditions from variation within the results. The S/N ratio is treated as a response (transform of raw data) of the experiment. In the present investigation, the S/N data analysis has been performed. The effects of the selected turning process parameters on the selected quality characteristics have been investigated through the plots of the main effects based on raw data. The optimum condition for each of the quality characteristics has been established through S/N data analysis aided by the raw data analysis. Taguchi recommends the use of the loss function to measure the performance characteristic deviating from the desired value. The rationale for this switch over to S/N ratios instead of working directly with the quality characteristic measurement is, the S/N ratio is a concurrent statistic –a special kind of data summery. A concurrent statistic is able to look at two or more characteristics of distribution and roll these characteristic into a single number or figure of merit. Usually, there are three categories of performance characteristic in the analysis of the S/N ratio. The loss function for the lower gives better performance characteristic and can be expressed as

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n} y^2{}_{ijk}$$

Where Lij is the loss function of the i^{th} performance characteristic in the j^{th} experiment,

y_{ijk} the experimental value of the i^{th} performance characteristic in the j^{th} experiment at the k^{th} trial, and

n the number of trials.

The loss function is further transformed into an S/N ratio. In the Taguchi method, the S/N ratio is used to determine the deviation of the performance characteristic from the desired value. The S/N ratio L^{ij} for the i^{th} performance characteristic in the j^{th} experiment can be expressed as

$$n_{ij} = -10\log(L_{ij}$$

Sr.no.	SPEED	FEED	DEPTH OF CUT	Ra	Calculated S/N ratio (db.)
1	1000	0.1	0.1	1.552	3.81783
2	1000	0.2	0.1	3.83	11.664
3	1000	0.3	0.1	4.905	13.8128
4	1000	0.1	0.2	2.47	7.85394
5	1000	0.2	0.2	3.564	11.0388
6	1000	0.3	0.2	2.795	8.92764
7	1000	0.1	0.3	1.272	2.08974
8	1000	0.2	0.3	3.07	9.74277

9	1000	0.3	0.3	4.091	12.2366
10	1250	0.1	0.1	1.7	4.60898
11	1250	0.2	0.1	1.415	3.01513
12	1250	0.3	0.1	3.936	11.9011
13	1250	0.1	0.2	2.216	6.9114
14	1250	0.2	0.2	2.98	9.48433
15	1250	0.3	0.2	3.783	11.5567
16	1250	0.1	0.3	2.056	6.26046
17	1250	0.2	0.3	3.276	10.3069
18	1250	0.3	0.3	4.954	13.8991
19	1500	0.1	0.1	2.021	6.11133
20	1500	0.2	0.1	1.998	6.01191
21	1500	0.3	0.1	1.2	1.58362
22	1500	0.1	0.2	2.397	7.59336
23	1500	0.2	0.2	2.738	8.74867
24	1500	0.3	0.2	2.946	9.38465
25	1500	0.1	0.3	2.559	8.16141
26	1500	0.2	0.3	1.803	5.11991
27	1500	0.3	0.3	3.425	10.6932

Table-5: The experimental results for surface roughness and its S/N ratio.

Results for the ANOVA performed using Minitab are given in the figures 3.1 shown below. They show the effect of the inputs on the output.

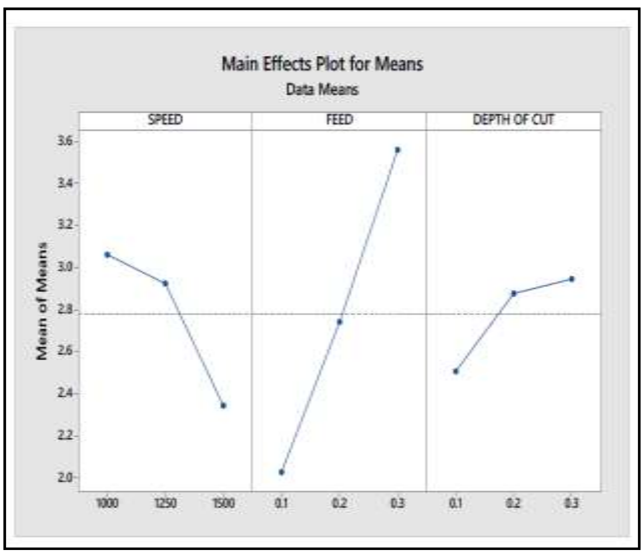

Fig-3.1: Main effect plots for work-piece surface roughness Ra (µm)

The main effect plot for the three different surface parameters Ra has been shown in figure 4.1. Figure 3.1 shows the main effect plot for work-piece surface roughness Ra for spindle speed, feed rate and depth of cut. Figure 3.2 shows the main effect plot for work-piece MRR for spindle speed, feed rate and depth of cut.

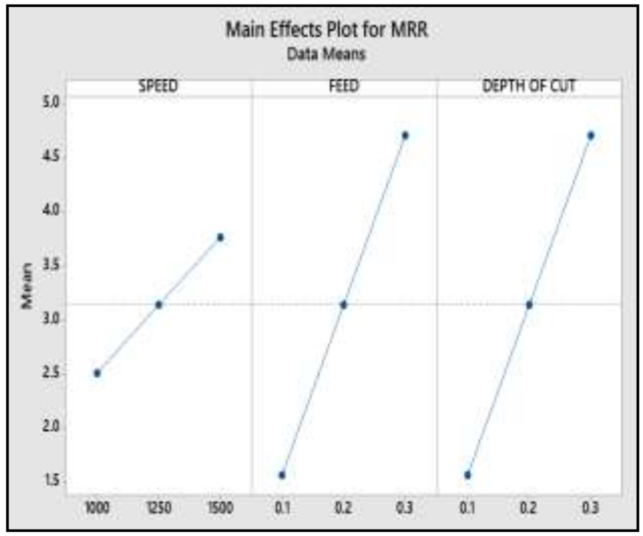

Fig-3.2: Main effect plots for work-piece MRR

Table-6: ANOVA result for work piece surface roughness

Source	Degree of freedom	Sum of Square	Variance	F ratio	P	% Contribution
Spindle Speed	2	7.106	3.553	7.13	0.005	6.710
Feed	2	44.413	22.207	44.55	0.000	41.938
Cut	2	44.413	22.207	44.55	0.000	41.938
Error	20	9.968	0.498			9.412
Total	26	105.901				

The high value of spindle speed, feed rate and depth of cut give high value of Material Removal Rate, i.e. high production rate. It was observed that the maximum MRR is obtained at the spindle speed 1500 RPM, 0.3 mm/rev of feed and 0.3 mm depth of cut.

Table-7: ANOVA result for work piece MRR cc/mi

Source	Degree of freedom	Sum of Square	Variance	F ratio	P	% Contribution
Spindle Speed	2	2.6156	1.3078	1.84	0.185	29.203
Feed	2	10.583	5.2919	7.44	0.004	37.241
Cut	2	1.0029	0.5014	0.71	0.506	23.528
Error	20	14.217	0.7109			10.026
Total	26	28.419				

4. ARTIFICIAL NEURAL NETWORKING

Backpropagation Algorithm:-

A key trigger for renewed interest in neural networks and learning was Werbos's (1975) backpropagation algorithm that effectively solved the exclusive-or problem by making the training of multi-layer networks feasible and efficient. Backpropagation distributed the error term back up through the layers, by modifying the weights at each node. In the mid-1980s, parallel distributed processing became popular under the name connectionism. Rumelhart and McClelland (1986) described the use of connectionism to simulate neural processes.

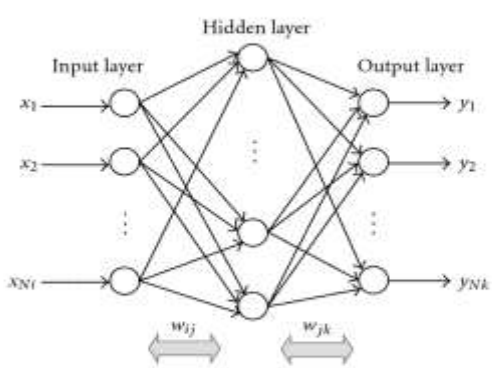

Fig-4.1: Backpropagation algorithm

Data of inputs and output of Surface finish is inputted to the MATLAB for all the 27 tests ran on the process. Data is been input by transposing it as ANN considers ever row as a parameter by default.

Sample data for inputs of 1 to 15 is also provided in the sample space for which results will be predicted. Set of sample data is shown in the figure 4.2 below.

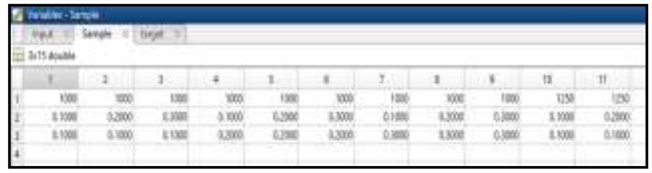

Fig-4.2: Sample data set variable

After that new network is created using input and target data with the settings as shown in below fig. 4.3, also hidden layer number of neurons is selected as 8. For selecting no of hidden neurons we takes different neuron sets such as 4, 6, 8 with respect to experimental data sets 1-15, 7-21, 13-27. We find less % of error from the 8 no of hidden neurons so we selecting the 8 no of hidden neurons.

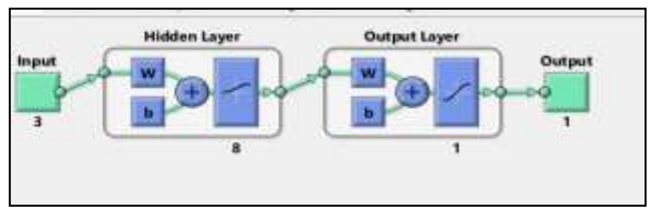

Fig-4.3: Hidden layer number of neurons.

After the network definition training info and parameters are set and training is done multiple times by checking the regression line values being within the acceptable limits.

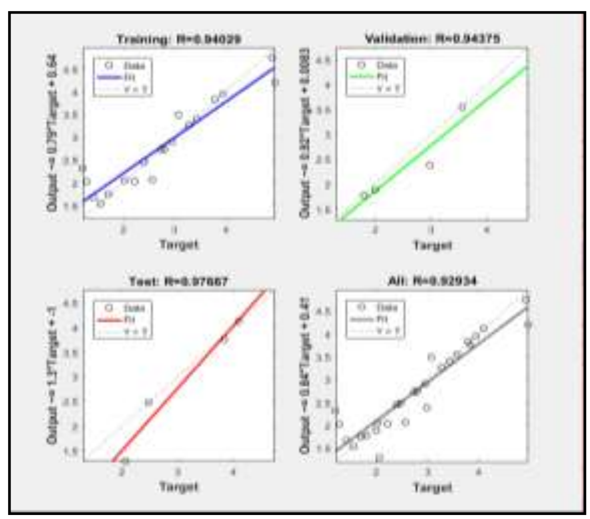

Fig-4.4: Regression plot for the training of ANN

SPEED	FEED	DEPTH OF CUT	Surface Roughness	SS ANN	Error
1000	0.1	0.1	1.55	1.49	4%
1000	0.2	0.1	3.83	3.83	0%
1000	0.3	0.1	4.91	4.50	8%
1000	0.1	0.2	2.47	2.34	5%
1000	0.2	0.2	3.56	3.42	4%
1000	0.3	0.2	2.8	3.05	-9%
1000	0.1	0.3	1.27	1.35	-6%
1000	0.2	0.3	3.07	3.30	-7%
1000	0.3	0.3	4.09	4.10	0%
1250	0.1	0.1	1.7	1.66	3%
1250	0.2	0.1	1.42	1.44	-1%
1250	0.3	0.1	3.94	3.60	9%
1250	0.1	0.2	2.22	2.16	3%
1250	0.2	0.2	2.98	2.95	1%
1250	0.3	0.2	3.78	3.82	-1%
1250	0.1	0.3	2.06	2.06	0%
1250	0.2	0.3	3.28	3.18	3%
1250	0.3	0.3	4.95	4.94	0%
1500	0.1	0.1	2.02	1.97	2%
1500	0.2	0.1	2	1.94	3%
1500	0.3	0.1	1.2	1.30	-8%
1500	0.1	0.2	2.4	2.31	4%
1500	0.2	0.2	2.74	2.85	-4%
1500	0.3	0.2	2.95	2.87	3%
1500	0.1	0.3	2.56	2.58	-1%
1500	0.2	0.3	1.8	1.82	-1%
1500	0.3	0.3	3.43	3.35	2%

Table-8: ANN output prediction of the surface roughness

Table shows the ANN output prediction of the surface roughness for all the observations we have performed testing on. Error Histogram is shown in the table 8 above. All the ANN readings predicted via software are close to the actual measured targets provided to the algorithm. Maximum error found during ANN is around 9 % which is within acceptance criteria of 10 % error.

The neural network has been designed with MATLAB 7.1 software. The back propagation algorithm is a gradient decent error-correcting algorithm

5. GENETIC ALGORITHM

The following outline summarizes how the genetic algorithm works:

1. The algorithm begins by creating a random initial population.
2. The algorithm then creates a sequence of new populations. At each step, the algorithm uses the individuals in the current generation to create the next population. To create the new population, the algorithm performs the following steps:

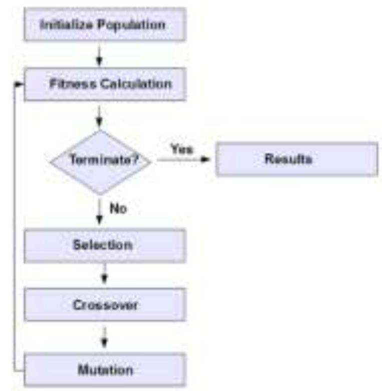

Fig-5.1: Steps in genetic algorithm

a. Scores each member of the current population by computing its fitness value. These values are called the raw fitness scores.
b. Scales the raw fitness scores to convert them into a more usable range of values. These scaled values are called expectation values.
c. Selects members, called parents, based on their expectation.
d. Some of the individuals in the current population that have lower fitness are chosen as elite. These elite individuals are passed to the next population.
e. Produces children from the parents. Children are produced either by making random changes to a single parent—mutation—or by combining the vector entries of a pair of parents—crossover.
f. Replaces the current population with the children to form the next generation.

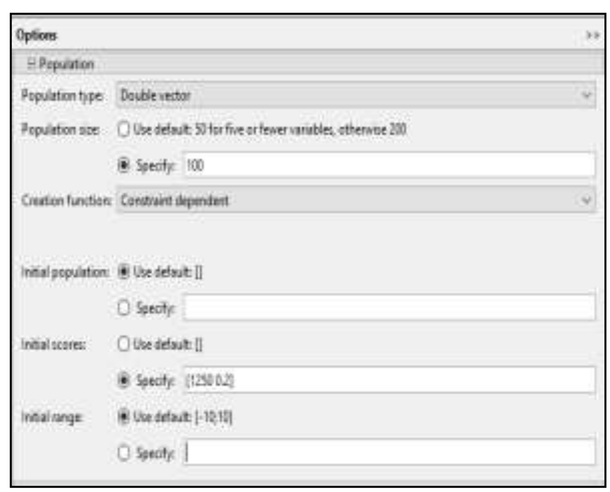

Fig-5.2: Population toolbox for GA

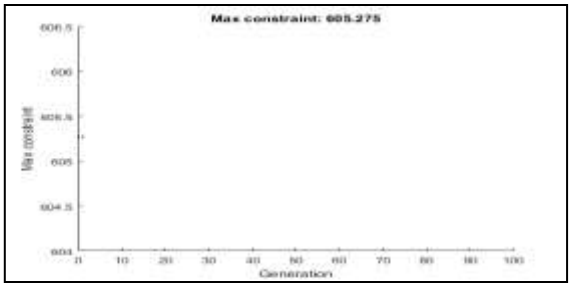

Fig-5.3: Maximum constraint plot

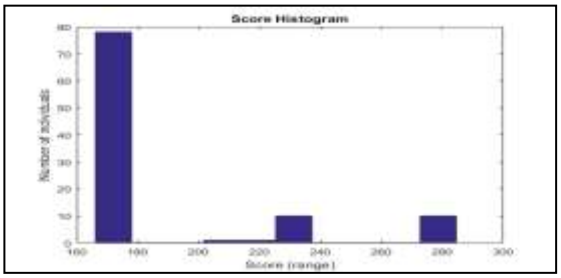

Fig-5.4: Score diversity plot

Sr.No.	SPEED	FEED	DEPTH OF CUT	Ra	GA
1	1000	0.1	0.1	1.552	1.822
2	1000	0.2	0.1	3.83	3.943
3	1000	0.3	0.1	4.905	4.99
4	1000	0.1	0.2	2.47	2.88
5	1000	0.2	0.2	3.564	3.987
6	1000	0.3	0.2	2.795	2.995
7	1000	0.1	0.3	1.272	1.322
8	1000	0.2	0.3	3.07	3.50
9	1000	0.3	0.3	4.091	4.291
10	1250	0.1	0.1	1.7	1.8
11	1250	0.2	0.1	1.415	1.545
12	1250	0.3	0.1	3.936	3.99
13	1250	0.1	0.2	2.216	2.88
14	1250	0.2	0.2	2.98	3.845
15	1250	0.3	0.2	3.783	3.983
16	1250	0.1	0.3	2.056	2.556
17	1250	0.2	0.3	3.276	3.576
18	1250	0.3	0.3	4.954	5.054
19	1500	0.1	0.1	2.021	2.521
20	1500	0.2	0.1	1.998	1.998
21	1500	0.3	0.1	1.2	1.321
22	1500	0.1	0.2	2.397	2.597
23	1500	0.2	0.2	2.738	2.938
24	1500	0.3	0.2	2.946	2.99
25	1500	0.1	0.3	2.559	2.789
26	1500	0.2	0.3	1.803	1.903
27	1500	0.3	0.3	3.425	3.725

Table-9: GA output prediction of the surface roughness

6. CONCLUSIONS

The results show that with the increase in spindle speed, feed rate and depth of cut there was a continuous increase in Material Removal Rate.

The results show that with the increase in spindle speed there is improve in surface roughness value up-to 1500 RPM. In the figure 3.1 the optimum value for speed 1350 for feed was 0.20 mm/rev and for depth of cut was 0.1 mm.

In the present work has been made to find a technique for optimizing machining parameter that could yield minimum machining time at the same time maintaining the desired surface roughness and MRR. Surface roughness and MRR value confidence level for the adequacy process occurs at cutting speed of 1500rpm, feed rate of 0.3mm/rev and depth of cut 0.1mm/rev is 1.20µm and 2.83cc/min respectively. Similarly the ANN and GA optimization technique find out same valve of cutting parameter with better surface finish 1.30µm and 1.32µm respectively. Artificial neural networking is successfully optimize and implied to the model and results of the surface finish predicted by ANN relation are in conformance with the observations made by actual testing with the error of maximum 9 %.

Method	Surface roughness (Ra)	Error (%)
ANOVA	2.78	6.474
ANN	2.64	1.5151
GA	2.90	10.3448
Practical	2.60	-

Table-10: Result Summery

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