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PREDICTION AND OPTIMIZATION OF SURFACE ROUGHNESS FOR END MILLING OPERATION USING ARTIFICIAL NEURAL NETWORKS AND GENETIC ALGORITHM

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ABSTRACT

This paper presents the work related the development of neural network model for predicting surface roughness and optimization of the process parameters for minimizing surface roughness using Genetic Algorithm. The process parameters chosen for this study are helix angle of tool geometry, spindle speed, feed rate, and depth of cut, while the output parameter is surface roughness. The experiments were conducted based on design of experiments using fractional factorial with 125 runs. The material and tool selected for this study is AISI 304 Austenitic Stainless Steel (AISI 304) and uncoated solid carbide end mill cutter respectively. Using the experimental data, feed-forward back propagation neural network model was developed and it was trained using the Levenberg– Marquardt algorithm. It was observed that the ANN model based on network 4-12-1 predicted surface roughness more accurately. To ensure optimization, a mathematical model was also developed to correlate the process parameters with surface roughness. A source code was developed in MATLAB to carry out the optimization. The optimized process parameters gave a value of 0.75132 μm for surface roughness.

Keywords: *Tool Geometry, Artificial Neural Networks, Fractional Factorial, Genetic Algorithm, Surface Roughness and End milling.*

1. Introduction

Austenitic stainless steels are widely used in cutlery, sinks, tubing, dairy, food and pharmaceutical equipments as well as in springs, nuts, bolts and screws due to their high strength and high corrosion and oxidation resistance. AISI 304 stainless steel finds its application in air craft fittings, aerospace components such as bushings, shafts, valves, special screws, cryogenic vessels and components for severe chemical environments. It is also being used for welded constructions in aerospace structural components [1]. Ciftci [2] investigated the machining characteristics of Austenitic Stainless Steels (AISI 304 and AISI 316) using multi layer coated carbide tools. The turning tests were conducted at four different cutting speeds at a constant feed rate and depth of cut. In manufacturing industries, milling is a fundamental metal-cutting operation and end milling is the most frequent operation encountered, which was employed for making profiles, slots, engraves, contours and pockets in various components. All end mills have a helix angle unless they are straight fluted tools. The helix angle is defined by angle formed by a line tangent to the helix and a plane through the axis of the cutter or the cutting edge angle which a helical cutting edge makes with a plane containing the axis of a cylindrical cutter. The grey–Taguchi method was adopted to optimise the milling parameters of aluminium alloy and found that tool geometry (helix angle) contribution percentage on surface roughness is 12.5% [3]. In the modern times, industries focus a lot on attaining dimensional accuracy and surface roughness of products. Surface roughness is an important parameter that influences mechanical properties such as fatigue behaviour, wear, corrosion, lubrication and electrical conductivity. It decides how the work piece components interact with its assembled parts. Obviously, rough surface will wear more and have high coefficient of friction than smooth surface hence surface roughness is a good predictor of quality of product. The demands for high quality of product relay on surface roughness urge the industrial automation to focus its attention on the surface finish of the product. Though surface roughness is a prominent parameter, it

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is expensive to control since the manufacturing cost will increase exponentially with decrease in surface roughness. An effective model to predict the surface roughness becomes essential to ensure the desired quality in end milling. Various studies have been made on the surface roughness in end milling using various tools, work materials and experimental methods. The literature survey pertaining to the work of other researchers is indicated here. Mathematical models to predict surface roughness in terms of machining parameters such as spindle speed, feed rate and depth of cut have been developed by many researchers [4-6].

Ginta et al. [7] employed central composite design of response surface methodology to develop an analytical model for surface roughness in terms of cutting parameters such as cutting speed, axial depth of cut and feed per tooth. Sivasakthivel et al [8] developed experimental evaluation of surface roughness for end milling of AI 6063 materials with high speed steel end mill cutter using response surface methodology (RSM) and neural network model. Ryu et al. [9] incorporated the effect of cutting edge angle on surface roughness and texture generation on end milled steel surfaces. They used RSM deviation, skewness and kurtosis for evaluating the characteristics of generated surface texture. The cutting performance of the end mill was assessed using variance analysis. Bhattacharya et al. [10] used Taguchi orthogonal array and analysis of variance to investigate the effect of cutting speed, feed rate and depth of cut on surface roughness and power consumption in high-speed machining. Ghani et al. [11] used Taguchi optimization methodology to optimize cutting parameters in end milling when machining hardened steel AISI H13 with TiN coated P10 carbide insert tool under semi-finishing and finishing condition of high-speed cutting.. Brezocnik et al. [12] proposed genetic programming approach to predict the surface roughness in end milling. Chang and Lu [13] proposed different polynomial networks for predicting surface roughness using the abductive modelling technique and the input variables selected based on F-ratio.

The technique of neural networks offer potential and an alternative to standard computer techniques in control technology and has attracted a huge interest in their development and application. The advantage of neural networks is that the network can be updated continuously with new data in order to optimize its performance. The network has the ability to handle a large number of input variables rapidly, filter noisy data and interpolate incomplete data [14]. A neural network modelling approach was presented by benardos and Vosniakos [15] to estimate the surface roughness in CNC milling process exploiting a number of experiments. Yang et al .[16] developed a Fuzzy-Nets-based in-process Adaptive Surface Roughness Control (FN-ASRC) system to adapt cutting parameters in-process to improve the surface roughness of machined parts. Lo [17] used adaptive-network-based fuzzy inference system to predict surface roughness in terms of spindle speed, feed rate and depth of cut. Jesuthanam et al. [18] developed a hybrid model by combining ANN with genetic algorithm (GA) in end milling operation to find the lower surface roughness. Oktem et al. [19] studied an effective ANN model integrated with GA optimization technique to determine the best combinations of cutting parameters that would minimize surface roughness in end milling of AISI 1040 steel with TiAIN solid carbide tools. A multilayered neural network was trained based on back-propagation learning algorithm and tested to control the performance of the trained ANN model. By adopting the tested ANN model with the powerful GA technique, optimization process was applied to achieve the lower surface roughness in terms of the best combinations of cutting parameters. Sureshkumar Reddy and Venkateshwara Rao [20] used GA to optimize tool geometry, viz., radial rake angle and nose radius and cutting conditions, viz., cutting speed and feed rate to obtain desired surface quality in dry end milling process of AISI 1045 steel specimens. A predictive model of surface roughness was created based on the experimentally measured values with cutting speed, feed rate, depth of cut and material removal rate and further optimised to obtain minimum surface roughness by neural network and genetic algorithm [21]. From the literature survey, the following can be inferred:

1. Though many studies have focussed on studying the different grades of austenitic stainless steels, the use of 304 grade stainless steel in end milling process, has not been studied much.

2 Most researchers have used cutting parameters like speed, feed and depth of cut as input parameters. Few researchers studied the combined effect of tool geometry (helix angle) with cutting parameters to predict the surface roughness. From the literature survey the effect of helix angle to predict the surface roughness has not been explored in detail.

2. A considerable amount of work has gone into studying the effect of process parameters on surface roughness, and most of them have used the regression models for predicting surface roughness.

4. Also, most researchers have used either central composite rotatable design or Taguchi design for conducting the experiments, which are suitable for developing regression models. On the contrary, for developing ANN model, further test data is required.

Hence, in this study, the experiments were conducted based on fractional factorial with 125 experimental runs.

Using the experimental data, a neural network model was developed with four neurons for the input layer, 12 neurons for the hidden layer and one neuron for the output layer. The chosen input parameters for developing the networks are helix angle (α), spindle speed (S), Feed rate (F) and depth of cut (D) respectively. The chosen output parameter is that of surface roughness (Ra).

The network was trained using Levenberg–Marquardt algorithm. It was found that ANN model based on network 4-12-1 predicted surface roughness more accurately. Genetic algorithm (GA) has been chosen for optimization as it can be applied to all kinds of objective functions. A source code was developed in MATLAB 7.6 for the purpose of optimization and the optimal process parameters gave a value of 0.75132 μm for surface roughness.

2. Experimental Procedure

The experiments were designed based on fractional factorial with 125 experimental runs [22], and were conducted as per the design matrix using HAAS vertical milling machine. AISI 304 Austenitic Stainless Steel work piece using an uncoated solid carbide end mill cutter with a diameter of 12 mm and 4 flutes. The tests were conducted along a 50 mm edge and the machining operations were carried out as per the conditions stipulated by the design matrix at random to avoid systematic error. The machined surface was measured at three different positions, and the averages of three measurements were taken as a response value. Surface roughness values (Ra) were taken using a Mitutoya surf test SJ-201 surf tester with 2.5 mm cut-off value. Radial depth of cut used in this work is 2.5 mm. The surface roughness measurement with Mitutoya surf test SJ 201 surf tester is shown in Figure 1.

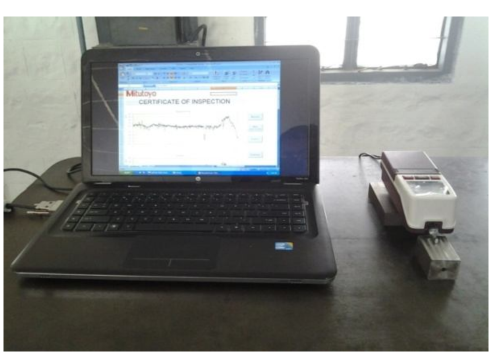


Fig. 1 Surface Roughness Measurement with Mitutoyo Surftest SJ 201 Surf Tester

3. Plan of Investigation

3.1 Identification of the process variables

Machining conditions set by various process parameters influence the surface roughnesses which in turn affect the overall quality. The identification of correct process parameters is of paramount importance in obtaining better surface finish with minimum effort. Desired surface roughness may be achieved by properly selecting the independently controllable process variables or factors which influence the surface quality.

Among the many independently controllable process parameters affecting surface roughness, helix angle of end mill cutter (α), Spindle speed (S), Feed (F) and depth of cut (D) are selected as factors to carry out the experimental works and the development of mathematical models.

Table 1: Machining Parameters and their Levels

Parameter	Unit & Notation	Levels				
		-2	-1	0	1	2
Helix angle	Degree (α)	25	30	35	40	45
Spindle speed	Rpm (S)	700	1400	2100	2800	3500
Feed rate	mm/rev (F)	0.03	0.06	0.09	0.12	0.15
Depth of cut	mm (D)	0.2	0.4	0.6	0.8	1.0

3.3 Development of design matrix

In factorial design, the experiments were conducted for all possible combinations of the parameter levels. These combinations were written in the form of a table where the rows correspond with different trials and the columns with the levels of the parameters. This forms a design matrix.

3.4 Recording the response

Roughness measurement was done using a portable stylus type profilometer, Mitutoya surf test SJ 201. The profilometer was set to a cut-off length of 2.5 mm, filter 2CR, traverse speed 1 mm/sec and 4 mm evaluation length. Roughness measurements, in the transverse direction, on the workpieces were repeated four times and average of four measurements of surface roughness parameter values was recorded. The measured profile was digitized and processed through the dedicated advanced surface finish analysis software (Mitutoyo ver 3.0) and profile is traced as shown in Figure 2. The design matrix and measured value of surface roughness are shown in Table 2.

Table 2: Design Matrix and Response

S.No	Machining parameters in coded values				Surface roughness (um)
	Helix angle (°)	Spindle speed (rpm)	Feedrate (mm/rev)	Depth of cut (mm)	
01	0	0	0	0	1.555
02	0	0	-1	2	1.539
03	0	0	0	1	1.558
04	0	0	1	0	1.669
05	0	0	2	-1	1.872
06	0	-1	0	2	1.4
07	0	-1	-1	1	1.504
08	0	-1	0	0	1.604
09	0	-1	1	-1	1.796
10	0	-1	2	0	1.94
11	0	0	0	1	1.558
12	0	0	-1	0	1.549
13	0	0	0	-1	1.536
14	0	0	1	0	1.669
15	0	0	2	2	1.881
16	0	1	0	0	1.43
17	0	1	-1	-1	1.308
18	0	1	0	0	1.43
19	0	1	1	2	1.728
20	0	1	2	1	1.866
21	0	2	0	-1	1.016
22	0	2	-1	0	1.223
23	0	2	0	2	1.607
24	0	2	1	1	1.54
25	0	2	2	0	1.565
26	-1	0	0	2	1.775
27	-1	0	-1	1	1.782
28	-1	0	0	0	1.785
29	-1	0	1	-1	1.88
30	-1	0	2	0	2.121
31	-1	-1	0	1	1.74
32	-1	-1	-1	0	1.828
33	-1	-1	0	-1	1.912
34	-1	-1	1	0	1.948
35	-1	-1	2	2	1.966
36	-1	0	0	0	1.785
37	-1	0	-1	-1	1.76
38	-1	0	0	0	1.785
39	-1	0	1	2	1.889
40	-1	0	2	1	2.124
41	-1	1	0	-1	1.544
42	-1	1	-1	0	1.654
43	-1	1	0	2	1.844
44	-1	1	1	1	1.874
45	-1	1	2	0	1.996
46	-1	2	0	0	1.459
47	-1	2	-1	2	1.831
48	-1	2	0	1	1.656
49	-1	2	1	0	1.573
50	-1	2	2	-1	1.582
51	0	0	0	1	1.558
52	0	0	-1	0	1.549
53	0	0	0	-1	1.536
54	0	0	1	0	1.669
55	0	0	2	2	1.881
56	0	-1	0	0	1.604
57	0	-1	-1	-1	1.676
58	0	-1	0	0	1.604
59	0	-1	1	2	1.514
60	0	-1	2	1	1.846
61	0	0	0	-1	1.536
62	0	0	-1	0	1.549
63	0	0	0	2	1.545
64	0	0	1	1	1.672
65	0	0	2	0	1.891
66	0	1	0	0	1.43
67	0	1	-1	2	1.608
68	0	1	0	1	1.53
69	0	1	1	0	1.544
70	0	1	2	-1	1.65
71	0	2	0	2	1.607
72	0	2	-1	1	1.42
73	0	2	0	0	1.229
74	0	2	1	-1	1.13
75	0	2	2	0	1.565
76	1	0	0	0	1.559
77	1	0	-1	-1	1.534
78	1	0	0	0	1.559
79	1	0	1	2	1.663
80	1	0	2	1	1.898
81	1	-1	0	-1	1.686
82	1	-1	-1	0	1.602
83	1	-1	0	2	1.404
84	1	-1	1	1	1.628
85	1	-1	2	0	1.944
86	1	0	0	0	1.559
87	1	0	-1	2	1.543
88	1	0	0	1	1.562
89	1	0	1	0	1.673
90	1	0	2	-1	1.876
91	1	1	0	2	1.618
92	1	1	-1	1	1.528
93	1	1	0	0	1.434
94	1	1	1	-1	1.432
95	1	1	2	0	1.77
96	1	2	0	1	1.43
97	1	2	-1	0	1.227
98	1	2	0	-1	1.02
99	1	2	1	0	1.347
100	1	2	2	2	1.947
101	2	0	0	-1	1.778
102	2	0	-1	0	1.791
103	2	0	0	2	1.787
104	2	0	1	1	1.914
105	2	0	2	0	2.133
106	2	-1	0	0	1.846
107	2	-1	-1	2	1.636
108	2	-1	0	1	1.752
109	2	-1	1	0	1.96
110	2	-1	2	-1	2.26
111	2	0	0	2	1.787
112	2	0	-1	1	1.794
113	2	0	0	0	1.797
114	2	0	1	-1	1.892
115	2	0	2	0	2.133
116	2	1	0	1	1.772
117	2	1	-1	0	1.666
118	2	1	0	-1	1.556
119	2	1	1	0	1.786
120	2	1	2	2	2.192
121	2	2	0	0	1.471
122	2	2	-1	-1	1.252
123	2	2	0	0	1.471
124	2	2	1	2	1.963
125	2	2	2	0	1.555

Fig. 2 Measured Surface Roughness Profile for Specimen 1

4. Model Development

The regression procedure was used for the developing mathematical model to predict surface roughness. The response function representing surface roughness can be expressed as Y = f (α, S, F, D), where Y is the response or yield. The second-order polynomial representing the response surface for ‘‘k’’ factors is given by Eqn. (2) [22].

$$Y = b_o + \sum_{i=1}^{k} b_i X_i + \sum_{\substack{i,\, j=1 \\ i \neq j}}^{k} b_{ij} X_i X_j + \sum_{i=1}^{K} b_{ii} X_i^2 \qquad (2)$$

where bo is the free term of the regression equation. The coefficients b_1, b_2, b_3 and b4 are the linear terms. The coefficients b_{11}, b_{22}, b_{33} and b_{44} are quadratic terms and the coefficients b_{12}, b_{13}, b_{14}, b_{23}, b_{24} and b_{34} are interaction terms.

Statistical software Quality America DOE PC IV [23] was used to calculate the values of these coefficients. The values of the regression coefficients gives an idea as to what extent the control parameters affect the response. The less significant coefficients are eliminated along with the responses with which they are associated, without compromising much on accuracy. This is done by using student’s t – test [24]. According to this test, when the calculated value of corresponding to the coefficient exceeds the standard tabulated value for the probability criterion kept at 0.75, the coefficient becomes significant otherwise it becomes insignificant. The final mathematical model was developed solely using the significant coefficients. The final mathematical model as determined by the above analysis is shown in Eqn (3) as follows

$$\text{Surface roughness (Ra)} = 1.555-0.113\alpha-0.087S+0.06F+0.011D+0.117\alpha^2-0.038S^2+0.054F^2-0.008D^2+0.097SD \qquad (3)$$

5. Development of neural network model

Artificial neural networks, one of the most powerful computer-modelling techniques based on statistical approach, currently being used in many fields of engineering for modelling complex relationships that are difficult to describe with physical models. The attraction of neural networks comes from their remarkable information, processing characteristics pertinent mainly to nonlinearity, high parallelism, fault and noise tolerance, and learning and generalized capability. There has been continual increase in research interest in the application of artificial neural networks in modelling and monitoring of machining processes. The objective of this study was to model the surface roughness of 304 grade stainless steel specimen.

5.1 Feed-forward neural network model

The network used here for predicting surface roughness is a feed-forward back propagation network. The network is a multilayer network. It consists of an input layer used for feeding the input data of the experiment, an output layer used for generating the response and at least one hidden layer used as training function to process the input data and yield output. This network uses network training function that updates weights and bias values, according to the gradient descent to reduce error.

Data obtained from the experiments were provided to a network at the learning stage, i.e., machining parameters and surface roughness values. During network learning, the network output was compared with the desired output and the connector weights inside the network were adjusted to minimize the difference. The error was then propagated backwards through the network and weights were changed, based on the feed forward back propagation learning algorithm. This learning process is an iterative one, and was stops once an acceptable error was reached. When the trained network was presented with new input (beyond training), the network responded according to the knowledge it acquired [25, 26].

6. Training the Neural Network

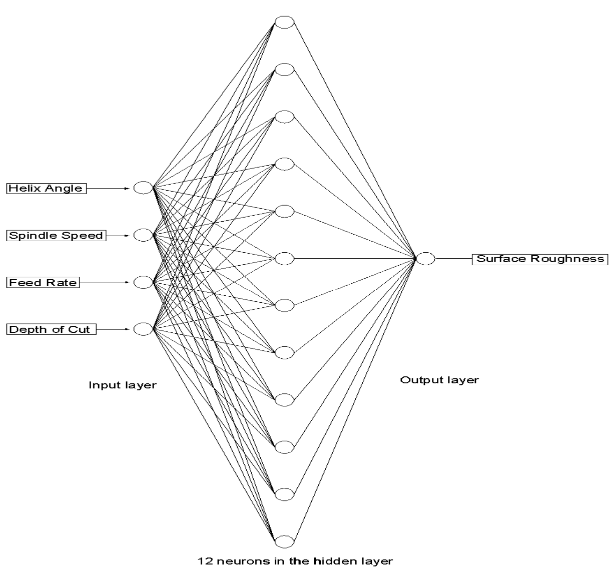
In this study, the input parameters used were the four main parameters, i.e., Helix angle (α), Spindle speed (S), Feed rate (F) and Depth of cut (D). The output parameter was the response, i.e., Surface roughness. In total, 125 experimental data were collected for building the neural network model. In order to relieve the training difficulty and balance the importance during the training process, the data should be normalized. The data are normalized between slightly offset values such as 0.1and 0.9 rather than between 0 and 1 to avoid saturation of the sigmoid function leading to slow or no learning. The normalized values for each row of input and output data set were calculated using Eqn. (4) [27]

$$X_i = 0.1 + 0.8\left(\frac{z_i - z_{min}}{z_{max} - z_{min}}\right) \qquad (4)$$

Where

Xi	=	Normalized input/output value
Zi	=	Actual input/output value
Zmax	=	Maximum input/output value
Zmin	=	Minimum input/ output value

A feed forward back propagation artificial neural network model was created keeping four neurons in the input layer, one neuron in the hidden layer and one neuron in the output layer by using MATLAB 7.6 [28]. The number of neurons in the hidden layer varied between 1 and 25 and they had to be decided based on trial and error. This was determined by gradually the increasing the number of neurons and observing their effect on the predicted value. Finally, the structure of the network selected was 4 -12 -1 (4 neurons in the input layer, 12 neurons in the hidden layer and 1 neuron in the output layer). The network architecture is shown in Fig. 3.



There is no specific rule available on how many data could be used for training and how much for testing and validation. The general guide line is that the training data should be more than testing and validation. Hence out of 125 experimental data 70% was used for training, 15% for testing and another 15% for validation. Thus in total, 88 data were used for training, 19 data for testing and 18 data for validation.

7. Testing the Neural Network

The network was trained to determine the performance of the established model of surface roughness. During training each time a set of inputs X_i of a training sample was presented and the corresponding output Y_o (predicted values) was obtained. The predicted value of the network model was compared with the actual value (Y_d). The comparison was done by calculating the mean sum of the squared error (MSE) between Y_d and Y_o using Eqn (5)

$$MSE = (Y_d - Y_o)^2 \qquad (5)$$

The objective of the algorithm is to minimize the mean sum of squared error for the entire experimental data. In this study, the net work was trained for 103 iterations. Further training did not seen to improve the modelling performance of the network. The average MSE obtained was 0.00031084, which shows that the model is very accurate. The performance goal of the network is displayed in Fig. 4.

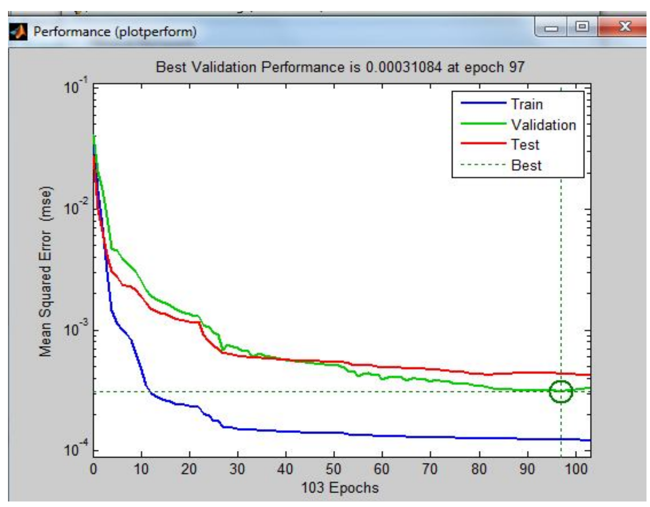


Fig. 4 Performance Goal of the Network

The percentage of error of the neural network model was calculated as the percentage difference between the experimental and predicted value relative to the predicted value. The result indicates that the percentage error falls within the range of 0.0457% to -5.321%, as displayed in Fig. 5.

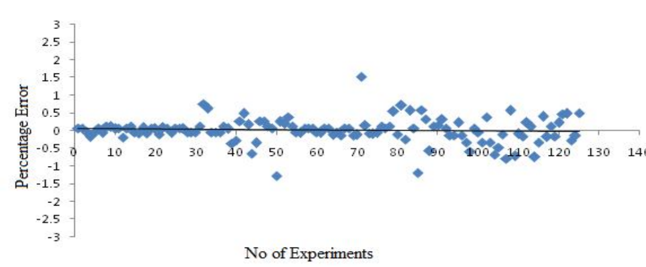


Fig. 5 Error Graph

The regression analysis was carried out to find out the correlation coefficient, which was used to measure the relationship between the measured and predicted values. The R value of '1' indicates a close relationship and '0', a random relationship. It was observed that a regression coefficient of R = 0.99395 was obtained for training data, R = 0.99003 for testing data, R = 0.99099 for validation data and R = 1 for the entire set of data. Hence, it can be deduced that this model is helpful for accurate prediction of surface roughness. The line of best fit was calculated using the regression coefficients, as shown in Fig.6.

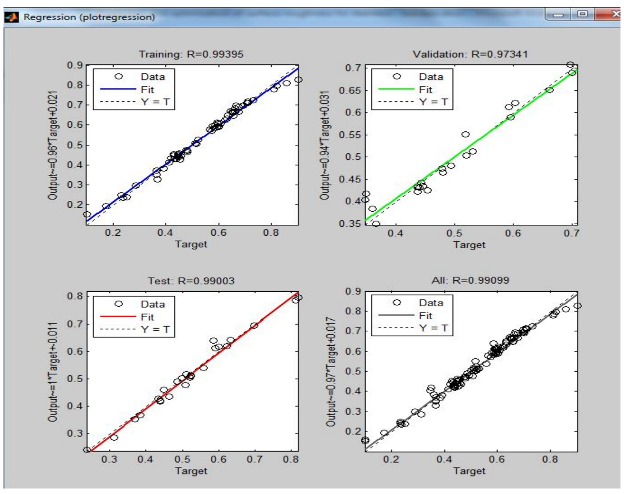


Fig. 6 Regression Graph for Observed and Predicted Values of Surface Roughness

7.1 Validity of the Neural Model

The validity of the neural model was tested by conducting additional tests, as shown in Table 3. From the above table, it can be inferred that the error percentage for additional tests falls within the range of 0.046 to -5.321%. Hence, the above model is can be effectively used for predicting surface roughness.

8. Effects of Process Parameters on Surface Roughness

The influence of the process parameters on the surface roughness was studied using the developed model. The direct effect of process parameters was studied by keeping all the process parameters at the middle level, except those parameters whose direct effect were being studied. The direct effects of all the parameters on surface roughness are discussed below

8.1 Direct effect of helix angle

From the figure 7, it can be observed that the surface roughness (Ra) decreases with an increase in helix angle. The use of helical cutter instead of a straight one helps to eliminate chatter vibration [29]. It is obvious that when chatter vibration decreases, surface roughness decreases. Further, increasing the helix angle above 400 increases the surface roughness. This could be attributed to the weakening of the teeth at higher helix angle, resulting in an increased surface roughness. From the Figure 5, it is evident that the surface roughness is optimum when the helix angle ranges from 350 to 400 and it is at its maximum at 250.

Table 3: Confirmatory Tests for Validity of Neural Model

Trial No	Machining Parameters in Coded Values				Surface roughness µm		Percentage Error
	α (0)	S (rpm)	F (mm/rev)	D (mm)	Observed Values	Predicted Values	
01	2	2	2	2	2.186	2.185	0.046
02	1	1	1.5	1	1.741	1.746	- 0.258
03	0	1.5	-1	1.5	1.529	1.549	-1.357
04	-1	-2	0	0.5	1.686	1.714	-1.631
05	2	-1	-0.5	-0.5	1.853	1.871	-0.944
06	0	0.5	1	1.5	1.602	1.687	-5.321

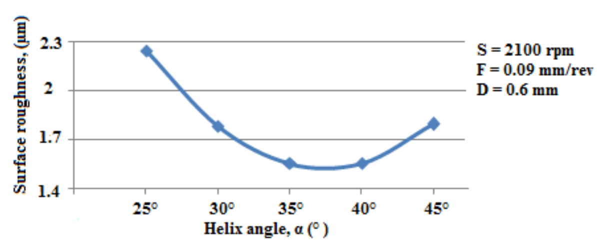


Fig. 7 Direct Effect of Helix Angle

8.2 Direct Effect of Spindle Speed

From Figure 8, it can be observed that the spindle speed has a significant effect on surface roughness. Also, it can be bserved that when spindle speed ranges from 700 rpm to 1400 rpm, the surface roughness slightly increases with an increase in spindle speed. Further increase in spindle speed up to 3500 rpm decreases the surface roughness. This is in accordance with the results obtained by [8]. Further, as stated by him, an increase in spindle speed results in reduced cutting time, which in turn minimizes the propagation of tool wear and surface roughness. From Figure 6, it is evident that the surface roughness is optimum when the spindle speed is 3500 rpm and it is at its maximum at 1400 rpm.

8.4 Direct effect of depth of cut

The effect of depth of cut (D) on surface roughness (Ra) is shown in figure 10. When the depth of cut ranges from 0.2 mm to 0.8 mm, the surface roughness can also be found to increase. When the depth of cut is lower, there is less work piece material adhered to the flank of the tool than at larger depth of cut. Since the heat and the forces generated during the cutting process are higher at larger depth of cut. Therefore, it can be inferred that higher temperature and higher forces are the main reasons that cause the adhesion of work piece material onto the tool flank face; which in turn accelerates tool wear and surface roughness [30]. But with an increase in depth of cut (D) beyond 0.8 mm, surface roughness (Ra) also shows a moderate decrease. From Figure 8, it is evident that the surface roughness is optimum when the depth of cut is 0.2 mm and it is at its maximum at 0.8 mm.

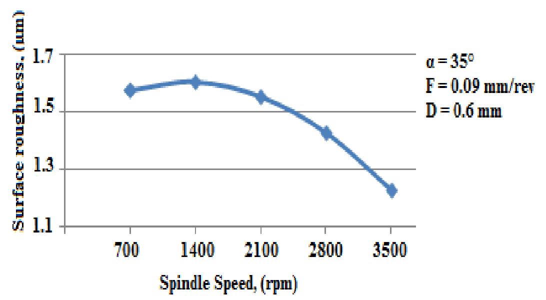


Fig. 8 Direct Effect of Spindle Speed

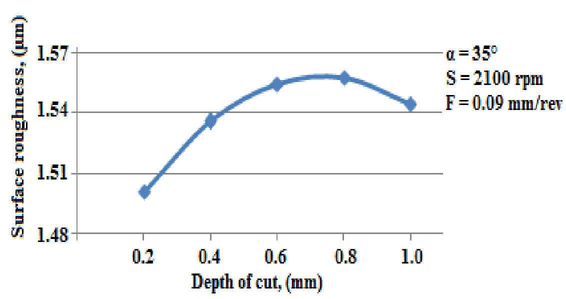


Fig. 10 Direct effect of depth of cut

9. Optimization Methodology Using GA Technique

The GA (Genetic algorithm) is a powerful and robust tool in solving optimization problems in the engineering mathematics and the other fields. GAs are computerized searching and optimization algorithms based on Darwin's evolutionary computation technique which presents the idea of "survival fittest" and "natural selection" [31-32].

The GA hopes to converge on the better solution by beginning with a set of potential solution changing them through several generations. This process starts with a potential solution of chromosomes (usually in the form of binary string) which are created or chosen at random. The entire set of these chromosomes evolve during several generations or iterations. New generations are created using the crossover and mutation operators. Crossover performs splitting two chromosomes and then integrating one half of each chromosome with the other pair. Mutation is carried out by flipping a single bit of chromosome. The chromosomes are then evaluated utilizing a fitness criterion and the best ones are saved while the other is thrown. The process completes once a near optimum solution that has a fitness value, is found. The flowchart of GA searching procedure is briefly illustrated.

9.1 Optimization of surface roughness with GA

The best selection of cutting parameters improves not only the benefit for end milling cost, but also the surface quality to a large extent by minimizing the roughness value. in the present study, an effective ga is developed to determine the best combinations of cutting parameters given in table by exploiting global optimization method. the problem of optimization of cutting parameters can be described by minimizing surface roughness as objective function. The present optimization problem is stated as follows:

9.2 Results of GA

Figure 11 shows the results obtained by running GA source code in MATLAB 7.6. The initial variation in the curve is due to the search for an optimum solution. It is evident that minimum surface roughness of 0.75132μm is observed at 30th iteration and converges to the same value up to 52 iterations. The optimum values of the process variables obtained from GA are given below:

Find Ra = [α,S,F,D] to minimize f (Ra) = (α,S,F,D)

Subject to cutting parameters:

$5 \leq \alpha \leq 45$ (°)

$700 \leq S \leq 3500$ rpm

$0.03 \leq F \leq 0.15$ mm/rev

$0.2 \leq D \leq 1.0$ mm

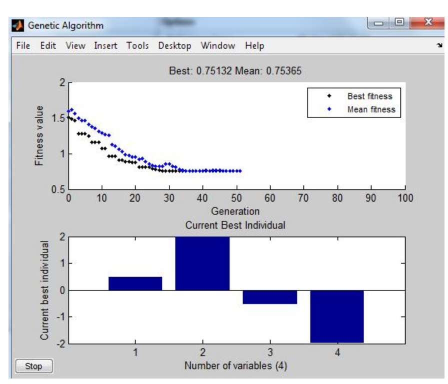


Fig.11 Best Fitness value

The optimum values of the process variables obtained from GA are given below:

1. Helix angle = 36.30(°)
2. Spindle speed = 3497 rpm
3. Feed rate = 0.0733 mm/rev
4. Depth of cut = 0.2044 mm

10. Conclusions

The investigation of this study indicates that the parameters helix angle, spindle speed, feed rate and depth of cut are the primary factors influencing the surface roughness of AISI 304 stainless steel during end milling. The following conclusions were arrived at from the present investigation:

i. Neural network model developed in this work from experimental data and GA-based optimization used in this work, it is possible to control the process to achieve the desired surface quality in the end milling process.
ii. It was observed that a regression coefficient of R = 0.99395 was obtained for training data, R = 0.99003 for testing data, R = 0.99099 for validation data and R = 1 for all the data. Hence, there exists a close relationship between the experimental and the developed model.
iii. Fractional factorial technique with 125 experimental runs can be effectively used for conducting experiments to collect experimental data for developing an ANN model.
iv. The minimum surface roughness obtained from experimental studies was 1.016 µm when the process parameters such as helix angle, spindle speed, feed rate and depth of cut were at 36°30´, 3497 rpm, 0.0733 mm/rev and 0.2044 mm respectively.
v. The optimization of process parameters was done using a GA and source code was successfully developed in MATLAB 7.6 for doing the optimization.
vi. The optimal process parameters gave a value of 0.75132 µm for surface roughness, which demonstrates the accuracy and effectiveness of the developed model.

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