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Prediction of Surface Roughness of Mild Steel Alloy in CNC Milling Process Using ANN and GA Technique

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ABSTRACT

In this paper, Analysis Of Variance (ANOVA), Artificial Neural Network (ANN), and Genetic Algorithm (GA) have been studied to predict the effect of milling parameters on the Surface Roughness (Ra) during machining of mild steel alloy. The milling experiments carried out based on the Taguchi design of experiments method using (L16) orthogonal array with 3 factors and 4 levels. The influence of three independent variables such as spindle speed (910, 930, 960, and 1000 rpm), feed rate (93, 95, 98, and 102 mm/min), and Tool Diameter (8, 10, 12, and 14 mm) on the Surface Roughness (Ra) were tested and analyzed with (ANOVA) to predict the response which indicates that spindle speed was the most significant factor effecting on Surface Roughness (Ra). Artificial Neural Network (ANN) and numerical methods are used widely for modeling and predict the performance of manufacturing technologies. Neural Network technique with 2 hidden layers, 10 neurons size, 1000 epochs, and Trainlm transfer function is used to predict the result. The Genetic Algorithm (GA) has been utilized to find optimal cutting conditions during a milling process.

From the results, the optimal value of spindle speed is (930 rpm), feed-rate is (95 mm/min) and tool diameter is (8 mm). This network structure is capable of predicting the Surface Roughness (Ra) well to optimize the milling parameters. Artificial Neural Network (ANN) predicted results indicate good agreement between the experimental and the predicted values.

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1. INTRODUCTION

Milling is the most widely used process in the machining of metals in the present industry. Several parts must be machined in at least one stage of their fabrication on milling machines. CNC milling is one of the most commonly used for its versatility and flexibility that allows the manufacture of products in a shorter time at a good finish and reasonable cost [1]. Identification of the optimum machining conditions is considered as a continual engineering task that aims to minimize the costs of production and achieving the required quality of the product. In the milling process, the surface roughness Ra is one of the most significant performance measures. For an efficient milling process, the smaller (Ra) is required which is considered as the factor that influences directly the hour rate of machining and the cost of production [2-4]. Due to this, the optimization of cutting parameters becomes very important. Recently, researchers attempt to optimize the conditions of machining utilizing different approaches such as Artificial Neural Network (ANN), Genetic Algorithm (GA), simulated annealing, gray relational analysis...etc. [5]. Considerable research has taken place on the surface finish for different situations. Several researchers have also utilized several methods, static methods for modeling Ra. Also, several methods or techniques have been employed to optimize process parameters. Recently, various scientific studies according to ANN and GA have been carried out because of its good predictive [1,6]. Amarta et al. conducted the optimization to detect the combination of process conditions in the vulcanization process utilizing the Back-Propagation Neural Network (BPNN) and GA. The total reduction of process quality lost cost was (Reduction of the process was Rp 238.55 or 27.30%) of quality loss cost before optimization [7]. Laot et al. conducted End-milling process conditions optimization on Carbon Fiber Reinforced Polymer (CFRP) using GA and Back Propagation Neural Network (BPNN) for predicting surface roughness and cutting force. The prediction error using BPNN is 0.0073%, while the most optimal network structure is (2) hidden layers with (10 x 2) nodes in each layer [8]. Jabir Mumtaz et al. focused on minimum quantity lubrication–assisted milling process on AISI 1045 material Surface Roughness and power consumption using multi-objective optimization genetic algorithm and Response Surface Methodology (RSM). The power consumption was measured using a novel low-cost power measurement system. From the comparison between RSM and multi-objective optimization genetic algorithm results, both measured and predicted results have a close agreement depict that [9]. Amber Batwara and Prateek Verma (2016) established a new process model for predicting the MRR and Surface Roughness in various practical applications. Model equations for response MRR and surface roughness were predicted accurately by ANN approach and Minitab software which produce good prediction equal to (90) % for responses and can be utilized by any cutting according to machining process manufacture [10]. Miloš J. Madić et al. developed Taguchi optimized ANN model and presented high accuracy of prediction. Experiments and analyses have been shown that Artificial Neural Network (ANN) architectural and training parameters can be optimally calculated systematically, thus to avoid the procedure of error and long trials [11].

This work deals with the prediction of CNC milling parameters (spindle speed (rpm), feed rate (mm/min), and tool diameter (mm)) influencing the desired output Surface Roughness (Ra) using Artificial Neural Network (ANN) and Genetic Algorithm (GA).

2. EXPERIMENTAL WORK

I. Selection of Material

Mild steel alloy is considered as one of the extremely versatile and flexible material and its use in many industries because of its good mechanical strength and low cost. Generally, mild steel has low elasticity. However, it is easy to form when machining. The dimension of each workpiece is (100 mm, 100 mm, 20 mm) as illustrated in Figure 1. Table I illustrates the chemical composition of the used alloy.

Figure 1: Workpiece Sample of Mild Steel Alloy

TABLE I: Chemical Composition of mild steel alloy

Sample	Workpiece material
C%	0.16
Mn%	0.786
P%	0.0107
Si%	0.19
Mo%	0.002
S%	0.0114
Cu%	0.0187
Cr%	0.0346
Al%	0.0351
Ni%	0.0069
Fe%	Bal.

II. Selection Parameters and Their Levels

The CNC machines play a major role in the modern machining industry to increase productivity within lesser time. CNC milling machine (CNC ACCUWAY UM-85) was used in this study as shown in Figure 2. To perform (8mm) cylindrical pocket on mild steel workpiece under the cutting conditions by High-speed steel, four flutes milling cutter. Tool Diameter (mm), feed rate (mm/ min), and Spindle Speed (rpm) were taken as process parameters and each parameter is specified at four levels. The process parameters and their levels are given in Table II.

Figure 2: (CNC ACCUWAY UM-85) milling machine

TABLE II: Process Parameters and Levels

Sr. No.	Process Parameter	Levels			
		1	*2*	*3*	*4*
1	Spindle Speed (rpm)	910	930	960	1000
2	Feed Rate (mm/min)	93	95	98	102
3	Tool Diameter (mm)	8	10	12	14

3. EXPERIMENTAL DESIGN AND OPTIMIZATION

I. Taguchi Approach and Experimental Design method

Design of Experiments using Taguchi method produces an efficient, simple, and systematic approach for determining the optimum conditions of machining in the manufacturing process [12]. In this work, tool diameter (d), feed-rate (f), and spindle speed (N) were considered for determining the effect of machining parameters on the surface roughness (Ra). Signal to Noise (S/N) ratio was used through Taguchi method to measure the characteristic of performance which deviate from the required values. (S/N) the ratio has been calculated according to Taguchi's (Smaller-The-Better) approach which aims to minimize Surface Roughness according to Eq. (1) [13]. Table III shows Taguchi orthogonal L_{16} Array and Experimental Results. Figure 3 shows the main effect plot of signal to noise ratio.

Smaller – The - Better:

$$S/N = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} R_i^2\right) \quad (1)$$

Where:
n: measurements number.
yi: the value of the measured characteristics.

Surface roughness (Ra) calculations were repeated four times after machining at various positions and then the average value was taken. The calculated average values were utilized to represent the machined surface roughness (Ra). After experimentation, Ra is measured using a surface roughness tester (Pocket Surf) as shown in Figure 3.

Figure 3: The surface roughness tester (Pocket Surf)

TABLE III: Taguchi orthogonal L_{16} Array and Experimental Results

No.	Spindle speed (rpm)	Feed-rate (mm/min)	Tool Diameter (mm)	Ra (µm)	S/N Ratio (η)
1	910	93	8	2.45373	-7.7965
2	910	95	10	3.34325	-10.4834
3	910	98	12	3.27310	-10.4700
4	910	102	14	3.61680	-11.1665
5	930	93	10	2.35841	-7.4524
6	930	95	8	1.76498	-4.9348
7	930	98	14	2.77973	-9.1700
8	930	102	12	2.36470	-7.4755
9	960	93	12	2.85798	-9.2063
10	960	95	14	3.34822	-10.4963
11	960	98	8	2.65610	-8.4849
12	960	102	10	3.73110	-11.4367
13	1000	93	14	3.00837	-9.4850
14	1000	95	12	2.81423	-8.9872
15	1000	98	10	3.34031	-10.4757
16	1000	102	8	2.61681	-8.5371

II. Development of ANN Modelling

The Artificial Neural Network has a significant effect to predict linear and nonlinear problems in various areas of engineering. To model the relation between the dependent variable (surface roughness) and the independent variables (cutting parameters), the neural network model has been proposed to develop this relation [14].In this paper, the Hebbian learning rule in the Neural Network model consists of three input neurons and one output corresponding to (tool diameter (d), feed–rate (f), spindle speed (N)), and (Ra) respectively. The number of the hidden layer and the number of neurons equal to (2) and (10) respectively. The numbers of input parameters are equal to 3. Figure 4 shows the schematic view of the neural network used.

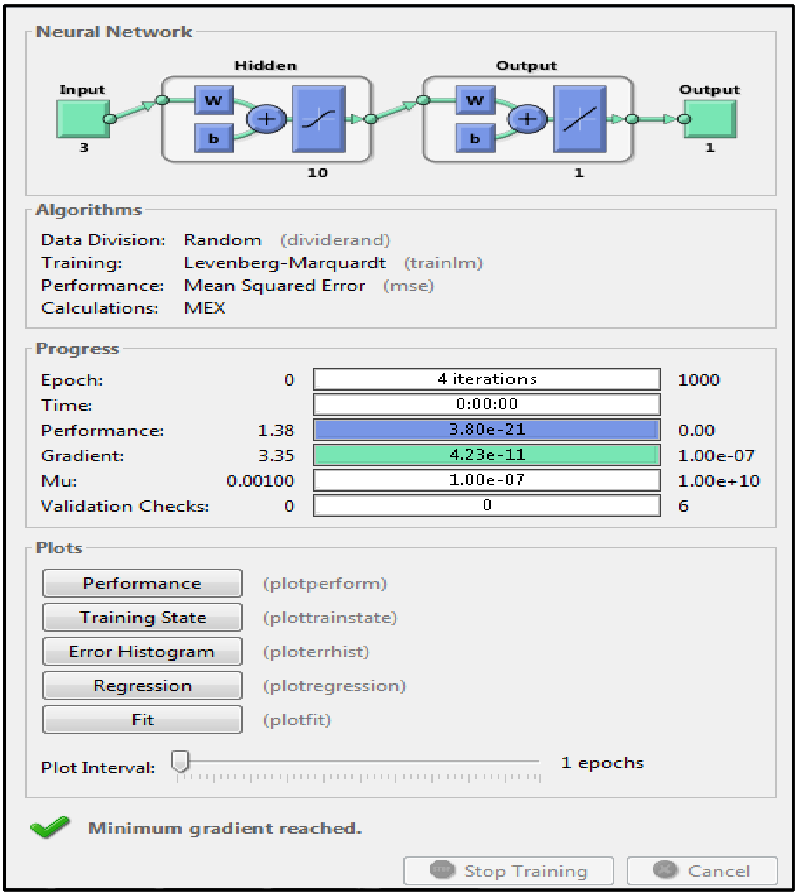

Figure 4: The schematic view of the neural network used.

III. Genetic Algorithm

Genetic Algorithm (GA) solves the problems of optimization by creating a group of possible solutions or population to the problem. Chromosomes that are the values of variables of the problem will be carried by the individuals in the population. Genetic algorithms are commonly utilized for generating high-quality solutions to search problems and optimization by relying on bio-inspired operators such as crossover, mutation, and selection. GA is an optimization technique that is utilized to find the best output for such inputs [5]. This method has been used by a majority of researchers due to its excellent results and fast response. The code for the GA was developed in MATLAB software for optimizing the milling process parameters to obtain minimum Surface roughness (Ra) [15].

In the present work, an optimization technique according to GA was implemented for optimizing the process parameters in the milling process and predicting the surface roughness (Ra).

4. Results

I. Analysis of Variance

According to the experimental results taken from Table III, the influence of input parameters on the Surface roughness (Ra) was analyzed by analyses of variance (ANOVA) from Taguchi approach using MINITAB 17 software. (ANOVA) was conducted to test the significance of the model when the P-value is less than 0.05 (95 % of confidence interval), then the model terms are statistically significant. Table IV illustrates ANOVA results for Ra.

TABLE IV:ANOVA results for Ra

Source	DF	Adj-SS	Adj-MS	F-Value	P-Value	% Contribution
N	3	1.90955	0.636518	104.92	0.000	46.118
F	3	0.42255	0.140849	23.22	0.001	10.205
D	3	1.80846	0.602820	99.36	0.000	43.677
Error	6	0.03640	0.006067			0.0398
Total	15	4.17696				100
	R-sq = 99.13%		R-sq(adj) = 97.82%		R-sq(pred) = 93.80%	

The overall significance of the mathematical model can be seen in Table 4, where (R-Sq) determines the fit value between the predicted and experimental results. (R-Sq(adj)) value means that the independent variable (N, f, and d) explain (99.75%) from the dependent variable (Ra), and the remaining leads to another factor like a random error. Figure 5, illustrate the Residual Plot for Ra (μm).

While, the mathematical model for Ra is developed below as shown in Eq. (2) to represent the relationship between the input parameters (N, f, and d) and the response (Ra).

$$Ra\ (\mu m) = 2.8955 + 0.2762\, N_{910} - 0.5785\, N_{930} + 0.2529\, N_{960} + 0.0494\, N_{1000} - 0.2259\, f_{93} - 0.0778\, f_{95} + 0.1168\, f_{98} + 0.1869\, f_{102} - 0.5226\, d + 0.2978\, d_{10} - 0.0680\, d_{12} + 0.2928\, d_{14} \qquad (2)$$

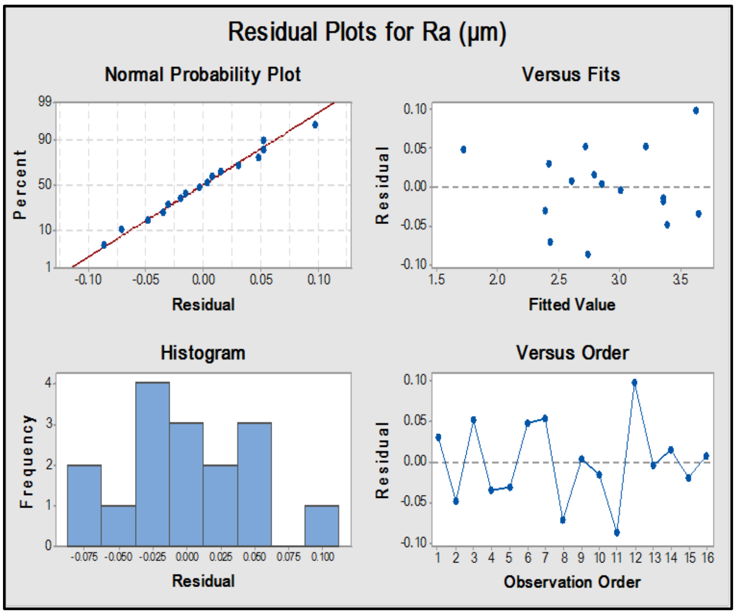

Figure 5: Residual Plot for Ra (μm)

II. Artificial Neural Network

An artificial neural network (ANN) is employed to create another predictive model and compare it with experimental and GA model results. The experimental database is utilized to construct the neural network. About 20% of data are utilized for model testing, whereas 60% of data are utilized for model training. The typical observation of the response of the output has been presented in Table V. Figure 6 shows the graphical representation of the proposed network.

TABLE V: Observation of the output response

Network Configuration	3 – 10 – 1 – 1
Type of transfer function	Trainlm
Epochs number	1000
Factor of learning rate (α)	0.1
Hidden neuron size	10
Hidden layer size	2
Number of trails for training	10
Number of trails for testing	3

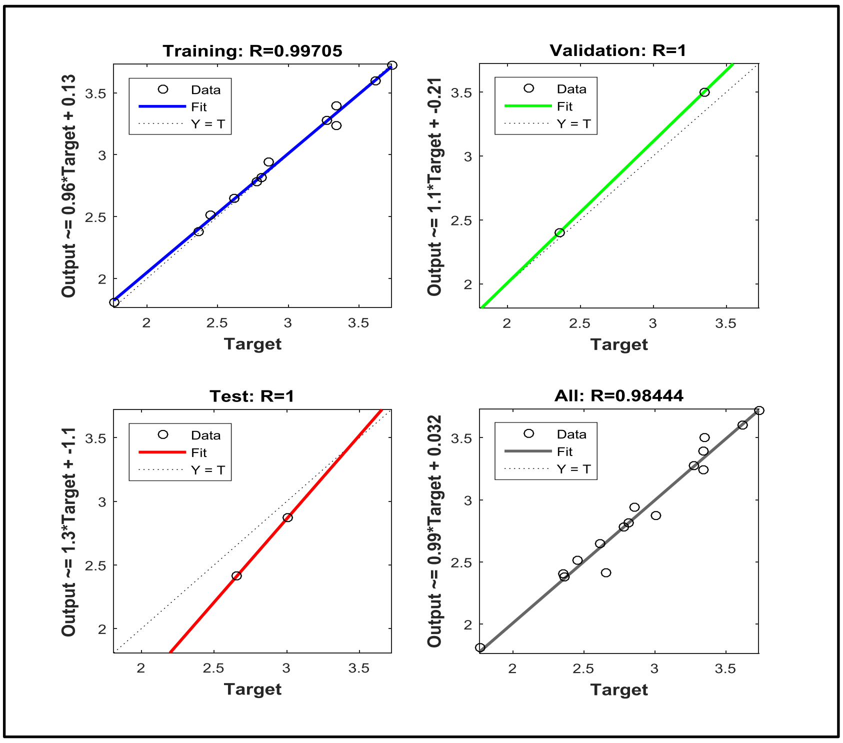

Figure 6: Graphical representation of the proposed

III. Optimization by GA

The present work function was optimizing the desired output (Ra) and process conditions by writing M-files in MATLAB software and solved by utilized GA. The optimization problem in the present study is the minimization of surface roughness and the constraints are spindle speed from 910 to 1000 (rpm), feed rate from 93 to 102 (mm/min), and tool diameter from 8 to 14 (mm). It is solved to obtain solutions by using a genetic algorithm in the optimization tool of Matlab R2013b. To obtain the best results with high accuracy, a group of generations was randomly chosen at population size (40, 60, and 80) at the range of operational conditions. Table VI illustrates the values of process conditions and the predicted response using GA for minimum Surface Roughness (Ra). The optimal value achieved for (Ra) and process conditions after utilizing GA as shown in Figure 7

TABLE VI:The predicted Surface Roughness (Ra) using GA

Exp. No.	Process variables			Ra
	Spindle speed (rpm)	Feed-rate (mm/min)	Tool Diameter (mm)	
		Population size 40		
1	930	102	10	2.9978
2	930	95	14	3.0925
3	930	102	14	3.4138
4	910	98	8	2.5822
5	1000	95	10	2.7605
		Population size 60		
6	930	95	8	2.4685
7	930	95	10	2.6795
8	1000	102	14	3.4978
9	960	98	12	3.0582
10	1000	102	10	3.0818
		Population size 80		
11	1000	102	8	2.8738
12	960	98	14	3.4498
13	930	98	10	2.6422
14	1000	95	10	2.7605
15	960	102	8	2.8258

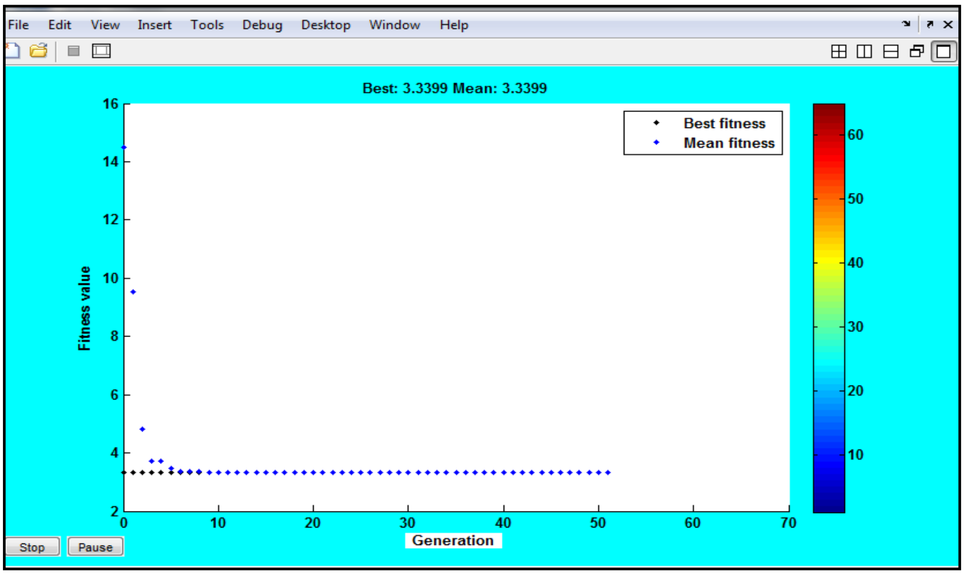

Figure 7: GA predicted result for Surface Roughness (Ra)

, terminated GA after 60 iterations with population size 40, probability of crossover 0.75 and probability of mutation 0.01 were selected, the best fitness was (3.33987) with Mean fitness equal to (3.33994). Table VII, Figure 8 presented a comparison between ANN and GA values with experimental values for surface roughness (Ra).

TABLE VII: Comparison between ANN and GA vs. Experimental values for Ra

No.	Average Ra (µm)	Predicted Ra (µm) by ANN	Percentage Error of ANN %	Predicted Ra (µm) by GA	Percentage Error of GA %
1	2.45373	2.45373	0.00000	2.4427	0.44952
2	3.34325	3.08527	7.71644	3.3335	0.29163
3	3.27310	3.27310	0.00000	2.9982	8.39876
4	3.61680	3.65914	1.17065	3.5898	0.74652
5	2.35841	2.45591	-4.13414	2.3347	1.00534
6	1.76498	1.76498	0.00000	1.5685	11.13214
7	2.77973	2.77973	0.00000	2.6302	5.3793
8	2.36470	2.36470	0.00000	2.3058	2.49080
9	2.85798	2.85798	0.00000	2.8287	1.0245
10	3.34822	3.23892	3.26442	3.1285	6.56229
11	2.65610	2.65610	0.00000	2.6422	0.52332
12	3.73110	3.73110	0.00000	3.5538	4.75195
13	3.00837	2.99285	0.51589	3.0047	0.12199
14	2.81423	2.81423	0.00000	2.7685	1.62496
15	3.34031	3.55190	-6.33474	3.3382	0.06317
16	2.61681	2.61681	0.00000	2.5938	0.87931

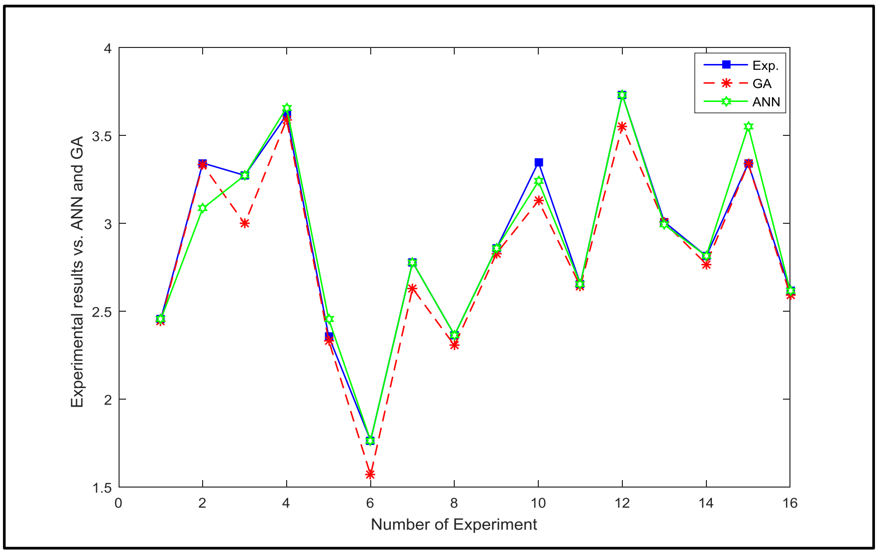

Figure 8: Comparison between experimental vs. ANN and GA predicted values for minimum (Ra).

5. CONCLUSIONS

i. In this Experimental study the milling experiments were implemented on CNC milling machine using a high-speed steel cutting insert under different cutting conditions for several groups of tool diameter (mm), feed rate (mm/min), and spindle speed (rpm).

ii. The milling test was performed based on Taguchi (L_{16}) orthogonal array. Both signals to noise ratio and ANOVA analysis were used to determine the optimal cutting parameters for Surface Roughness (Ra).

iii. The ANOVA results show that the most effective factor for Surface Roughness (Ra) was spindle speed with a percentage contribution of (46.118%), then the tool diameter and feed rate effected by (43.677 %) and (10.205%) respectively.

iv. The experimental data has been learned using ANN. Neural Network has been trained by using (10) patterns. The neural network model shows closed results matching between the actual calculated Surface Roughness (Ra) and the predicted output model as shown in figure (8).

v. The optimized Surface Roughness (Ra) value using GA was 3.3399 μm, So that this value is close to or equal to the optimized value should be selected. Where the lower surface roughness value can be obtained when spindle speed is (930rpm), feed is (95 mm/min) and tool diameter is (8 mm).
vi. It is clear that the average value of the percentage error for Surface Roughness (Ra) between GA and the experimental value is found to be (2.84034 %), while the average value of the percentage error between ANN model and the experimental value lies between (0.13741 %), which is less than the GA model significantly. However, if the test patterns number will be increased then this error can be further minimized.
vii. The proposed ANN and GA prediction model sufficiently predicts Surface Roughness (Ra) accurately. However, ANN prediction model is found to be better as compared to GA prediction model.

References

[1] D.B. prakash , G.R. Balaji , A.G. chand, V.A. kumar, D.V.N.Prabhaker, "Optimization of machining parameters for aluminium alloy 6082 in cnc end milling," International Journal of Eng. Research and Applications (IJERA), ISSN: 2248-9622, Vol. 3, Issue 1, pp.505-510, 2013.

[2] F. Puh, Z. Jurkovic, M. Perinic, M. Brezocnik and S. Buljan, "Optimization of machining parameters for turning operation with multiple quality characteristics using Grey Relational Analysis," Tehnicki vjesnik, vol.23, no.2, pp.377-382, 2016.

[3] M.S. Mahendra and B Sibin, "Optimization of milling parameters for minimum surface roughness using Taguchi method," IOSR Journal of Mechanical and Civil Eng. (IOSR-JMCE), e-ISSN: 2278-1684, p-ISSN: 2320-334X, pp.01-05, 2016.

[4] S. Sakthivelu, M. Meignanamoorthy, M. Ravichandran and M. Kumar, "Effect of machining parameters on surface roughness and material removal rate in CNC end milling," International Journal of Scientific

[5] ," ICONNECT Research and Eng. Studies (IJSRES), vol.2, Issue 4, ISSN: 2349-8862, 2015.

[6] P. Pothys, R. Selvam, and A. S. Kumar, "Evaluation of optimal machining parameters for turning by using genetic algorithm - 2k18, " Conference Proceedings, International Journal of Eng. Research & Technology (IJERT), ISSN: 2278-0181, Volume 6, Issue 07, 2018.

[7] A. Zerti , M.A. Yallese, O. Zerti , M. Nouioua and R. Khettabi, "Prediction of machining performance using RSM and ANN models in hard turning of martensitic stainless steel AISI 420," Journal of Mechanical Eng. Science, Vol. 0, No. 0, pp. 1–24, 2019.

[8] Z. Amarta, B. O Pramoedyo, S. Sutikno, and R. Norcahyo, "Multi response optimization in vulcanization process using backpropagation neural network-genetic algorithm method for reducing quality loss cost," AIP Conference Proceedings 2114, 2019.

[9] P. A. L. Laot, and S. Sampurno , "Multi-response optimization of cutting force and surface roughness in carbon fiber reinforced polymer end milling using back propagation neural network and genetic algorithm," AIP Conference Proceedings 2114, 2019.

[10] J. Mumtaz, Z. Li, M. Imran, Lei Yue, M. Jahanzaib, S. Sarfraz, E. Shehab, S. Oluwarotimi and K. Afzal, "Multi-objective optimization for minimum quantity lubrication assisted milling process based on hybrid response surface methodology and multi-objective genetic algorithm," Advances in Mechanical Eng., Vol. 11, No. 4, pp.1–13, 2019.

[11] A. Batwara and P. Verma, "Influence of process parameters on surface roughness and material removal rate during turning in CNC lathe – an Artificial Neural Network and surface response methodology," International Journal of Recent Advances in Mechanical Eng. (IJMECH), vol.5, No.1, 2016.

[12] M. J. Madic and M. R. Radovanovic, "Optimal selection of ANN training and architectural parameters using Taguchi method: A case study," FME Transations, vol.39, No.2, pp.79-86, 2011.

[13] S. Cetin and T. Kivak, "Optimization of the machining parameters for the turning of 15-5 PH stainless steels using the Taguchi method," Materiali in Technologiji, vol.51, No.1, pp.133-140, 2017.

[14] S. Karabulut, "Optimization of surface roughness and cutting force during AA7039/Al2O3 metal matrix composites milling using neural netwotks and Taguchi method," Measurement, vol.66, pp.139-149, 2015.

[15] M. M.H. AL-Khafaji, H. L. Alwan and B. M.H. Albaghdadi, "Roughness assessment for machined surfaces in turning operation using neural Network," Eng. & Tech. Journal, Vol.32, Part (A), No.5, 2014.

[16] S. Dave , Jay J. Vora , N. Thakkar , A. Singh, S. Srivastava, B. Gadhvi, V. Patel, A. Kumar, "Optimization of EDM drilling parameters for Aluminum 2024 alloy using Response Surface Methodology and Genetic Algorithm," Key Eng. Materials, ISSN: 1662-9795, Vol. 706, pp. 3-8, 2016.