International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-10 Issue-8, June 2021

Multi Objective Optimization of Machining Parameters in End Milling of AISI1020

Jignesh G. Parmar, Komal G. Dave

***Abstract:** In current research, artificial neural network (ANN) and Multi objective genetic algorithm (MOGA) have been used for the prediction and multi objective optimization of the end milling operation. Cutting speed, feed rate, depth of cut, material density and hardness have been considered as input variables. The predicted values and optimized results obtained through ANN and MOGA are compared with experimental results. A good correlation has been established between the ANN predicted values and experimental results with an average accuracy of 91.983% for material removal rate, 99.894% for tool life, 92.683% for machining time, 92.671% for tangential cutting force, 92.109% for power and 90.311% for torque. The MOGA approach has been proposed to obtain the cutting condition for optimization of each responses. The MOGA gives average accuracy of 96.801% for MRR, 99.653% for tool life, 86.833% for machining time, 93.74% for cutting force, 93.74% for power and 99.473% for torque. It concludes that ANN and MOGA are efficiently and effectively used for prediction and multi objective optimization of end milling operation for any selected materials before the experimental. Implementation of these techniques in industries before the experimentation is useful to reduce the lead time, experimental cost and power consumption also increase the productivity of the product.*

***Keywords:** Word; ANN; Prediction; MOGA: Multi Objective Optimization; Modelling; DOE.*

I. INTRODUCTION

The end milling operation is an important and common metal cutting operation in industries. The end milling operation makes use of in many industries like die making, biomedical components, automobile and aerospace. Many simple to complex geometry profiles have been produced through end milling. In end milling, the material has been removed by two continuous movements for tool and workpieces. The tool is in rotating movement and the workpiece is in straight ones. The expensive setup has been required in industries during the performed experimental process and it's very time-consuming. The manufacturer concentrated on the productivity, production time, cost and quality of the product. AI techniques used for the development of prediction models, i.e. simulated annealing, fuzzy logic, partial swan optimization, ANN, genetic algorithm [1].

Manuscript received on June 15, 2021.
Revised Manuscript received on June 20, 2021.
Manuscript published on June 30, 2021.
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ANN is an artificial intelligence technique used for modeling and simulation of metal removing processes [2]. MOGA is widely utilized for the multi objective optimization of conflicting machining variables [3]. In this paper, ANN and MOGA tool have been used for the prediction and multi objective optimization of end milling process parameters respectively. J.S.Pang et al. [2014] [4] investigation on halloysite nanotubes composite material for end milling operation. The Taguchi method has been used for optimization. Cutting force and surface roughness have been considered as output variables. The input variables like spindle speed, depth of cut and feed rate. N. Naresh et al. [2014] [5] optimized the CNC milling parameters utilizing the Grey-Taguchi method. In this study surface roughness is considered as a response parameter. The experiment has been conducted based on Taguchi's L27 orthogonal array. Nuraini Lusi et al. [2020] [6] achieved the combination of process variables for maximum material removal rate and minimum surface roughness. Taguchi method and grey relational analysis have been used for experimentation and optimization. Prediction of input variable has been found out using Grey Relational Grade. Optimized the responses concurrently with soluble oil, cutting speed of 5.13%, feeding speed of 39.8%, and depth of cut of 30.52%. Lohithaksha M Maiyar et al. [2013] [7] investigated on inconal 718 and used grey relational analysis for optimization. Taguchi L9 array used for experimentation. The most significant factor has been achieved through ANOVA. V.S.Kaushik et al. [2018] [8] focused on temperature rise during end milling cutting operation because it affected tool life, cutting force, vibration, tool deflection and quality of the machined parts. Doing statistical analysis based on cutting speed, depth of cut, feed rate, radial rake angle and helix angle under dry condition. Aluminum Al7068 and various tool geometry end mill have been selected for experimentation. A genetic algorithm has been used to optimize the process parameter to less rise of temperature. Jakeer Hussain Shaik et al. [2017] [9] used multi-objective genetic algorithms for optimization. Experiments have been carried out using the RSM for the machining of Al 6061 alloy. The M. Bhuvanesh Kumar et al. [2020] [10] used grey relational analysis and find out optimum cutting conditions for minimum surface roughness, cutting force and maximum material removal rate. The experiment has been carried out using Taguchi method and ANOVA used for the analysis of responses. Sivasakthivel P.S. et al.[2018] [11] determined the optimum value of helix angle, nose radius, rake angle, cutting speed, feed rate, depth of cut for a minimum value of surface roughness and tool wear.

Taguchi orthogonal array used for experimentation. ANOVA has been used for analysis. Optimum values of input parameters have been found out using grey-fuzzy logic algorithm given responses. It concludes that few works has been carried out for multi objective optimization and prediction of end milling operation for any materials before the experimental work. It is also revealed that material properties are not involved any artificial intelligence model.

II. METHODOLOGY

In this research, studied the relationship between the input variable, material properties and output variables of end milling operation for the mathematical model. This mathematical model has been used for the development of ANN model and MOGA.

A. *Development Of Mathematical Model*

In this study Cutting speed, depth of cut, feed rate, material density and hardness selected as an input variables and material removal rate, machining time, tool life, tangential cutting force, torque and power have been selected as a responses. The material removal rate (mm^3/second.) has been discovered using equation (1) [13].

$$MRR = \frac{Wi - Wo}{\rho \times T} \quad (1)$$

Where, Wi and Wo is the initial weight and final weight of the work piece, ρ is the material density and T is the machining time. Machining time (sec.) has been discovered using equation (2) [15].

$$T = \left(\frac{l + a + o + D/2}{f \times Zc \times n} \right) \times 60 \quad (2)$$

Where, l is work piece length, a is approach Distance, o is over run, D is cutter Diameter, f is feed rate in mm/tooth, Zc is total number of teeth of end mill, n is Spindle speed in rpm. Tool life has been discovered using equation (3) [14].

$$v \times T_l^n = c \quad (3)$$

Where, v is cutting Speed (m/min.), T_l is tool life in minutes, n and c are constants which depend on tool shape, work tool pair, cutting environment, etc. Tangential cutting force (kgf) has been discovered using equation (4) [17].

$$F = (Zs \times K \times A \times b) \quad (4)$$

Where Zs is a number of teeth with simultaneous engagement with the workpiece, K is specific cutting force in kgf which depends upon the material hardness, A is average chip thickness in mm and b is chip width in mm. Torque (Kgf·mm **)** has been discovered using equation (5) [17].

$$T_q = \frac{F \times D}{2} \quad (5)$$

Power (Kw) has been discovered using equation (6) [17].

$$P = \frac{F \times V}{6120} \quad (6)$$

The design of experiment is a systematic approach to discover the combination of cutting parameters for achieving desirable outputs for research attributes [12]. The full factorial design has been utilized for the design of the experiment. Minitab 17 has been used for level and factor combination, which provided 125 arrangements of input variables.

Table I Factors and levels for end milling operation

Factors	Cutting Speed in m/min.	Feed in mm/tooth.	DOC in mm
Levels	5	5	5
Values	140, 150, 160, 170, 180	0.12, 0.15, 0.18, 0.21, 0.24	0.2, 0.4, 0.6, 0.8, 1

The range of input variables chosen based on Design data book [16] is shown in Table I.

B. *Artificial Neural Network*

ANN work is based on our present understanding of the biological nervous system. Feed forward back propagation learning algorithm used in this ANN model. ANN model has been developed through MATLAB R2015a software. The ANN architecture with 5 input, 6 hidden and 6 output layers shown in Fig. 1. Here 10 neurons available in each hidden layer. The transfer function has been used to connect the layer and transfer the signal of one neuron to another neuron. TRAINLM was chosen as a training function and it rationalized through Levenberg-Marquardt algorithm. LEARNDGM and TANSIG have been selected as learning and transfer functions individually.

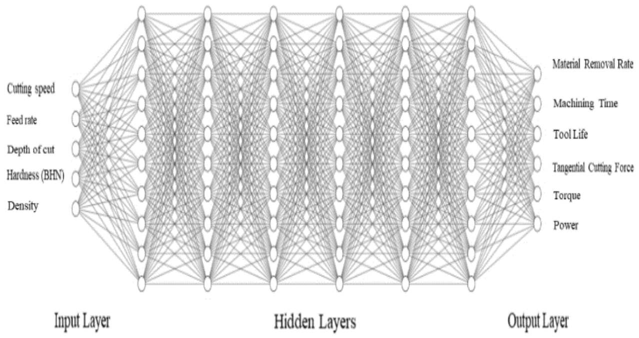

Fig. 1 ANN architecture

MSE consider as a performance function and 1000 epochs are selected to train the ANN model.

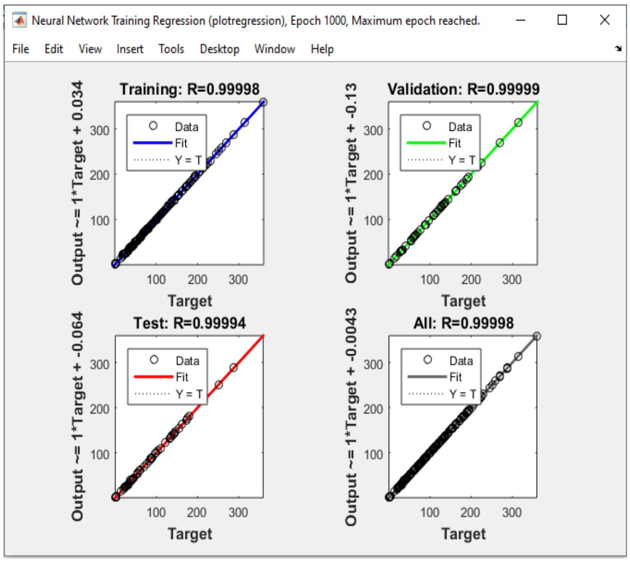

Fig. 2 ANN regression analysis

ANN model trained through 100 datasets than 25 datasets used to test the model. The regression value model is shown in Fig. 2. The correlation coefficient of 0.99998 has been achieved for the whole dataset which shows a good correlation. The best validation performance 0.14426 achieved at epoch 296 of the trained ANN model is shown in Fig. 3.

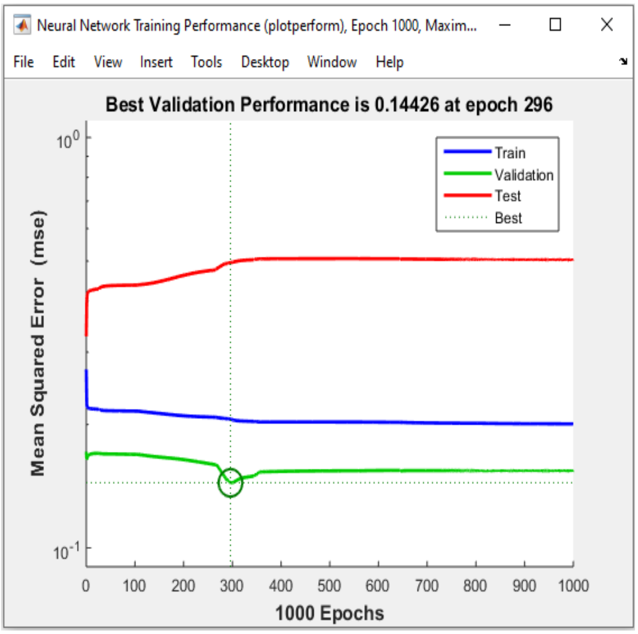

Fig. 3 Performance of trained neural network

C. Multi Objective Optimization

In engineering, industries involve multiple objectives instead of a single objective so that it's a challenging task to optimization of the problem with multiple conflicting objectives. MOGA tool with MATLAB R2015a has been utilized for optimization. The developed mathematical model has been utilized for non-dominated Pareto optimal solutions. In multi objective genetic algorithm, three main subordinates like reproduction, crossover and mutation have been used for optimization. The objective functions for maximizing the MRR and tool life shown in equations (7) and (8). The objective functions for minimizing the machining time, tangential cutting force, torque and power are shown in equations (9) to (12) respectively.

To maximize

$$MRR = \frac{(Wi - Wo)}{\left[\rho \times \left(\frac{1 + D/2 + D/2 + D/2}{f \times Zc \times n}\right) \times 60\right]} \tag{7}$$

$$T_l = \left[\frac{n}{v}\right]^{(1/C)} \tag{8}$$

To minimize:

$$T = \left(\frac{1 + D/2 + D/2 + D/2}{f \times Zc \times n}\right) \times 60 \tag{9}$$

$$F = \left[\frac{(Zs \times K \times d \times 57.3 \times f \times 2 \times 9.80665)}{60}\right] \tag{10}$$

$$T_q = \left[\left(\frac{(Zs \times K \times d \times 57.3 \times f \times 2 \times 9.80665)}{60}\right) \times \left(\frac{D}{2}\right)\right] \tag{11}$$

$$P = \left[\left(\frac{(Zs \times K \times d \times 57.3 \times f \times 2 \times 9.80665)}{60}\right) \times \left(\frac{V}{6120}\right)\right] \tag{12}$$

The constraint function of responses is shown in equation (13).

$$\begin{aligned}
&C = [25 - ((Wi - Wo)/(\rho \times ((l + (D/2) + (D/2) + (D/2))/(Zc \times f \times n)) \times 60));\\
&((l + (D/2) + (D/2) + (D/2))/(Zc \times f \times n)) \times 60 - 3.40;\\
&(15 - (n/v)^{(1/C)});\\
&((Zs \times K \times d \times 57.3 \times f \times 2 \times 9.80665)/60) - 364;\\
&(((Zs \times K \times d \times 57.3 \times f \times 2)/60) \times (D/2)) - 210;\\
&(((Zs \times K \times d \times 57.3 \times f \times 2)/60) \times v)/6120 - 0.95]
\end{aligned} \tag{13}$$

MOGA processing parameters and its values are shown in table II.

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Table II Multi objective genetic algorithm processing parameters

Processing parameters	Value and functions	
Total objective function	6	
Input variable constraint	14	
Size of population	50	
Number of generation	114	
Selection function	Tournament	
Size of tournament	2	
Creation function	Feasible population	
Constraint tolerance	1e-3	
Function tolerance	1e-4	
Migration fraction	0.2	
Cross over fraction	0.8	
Mutation function	Adaptive feasible	
Distance measure function	Distance crowding	
Crossover function	Single point	
Upper and lower bound	$140 \leq Vc \leq 180$	$376 \leq W1 \leq 376$
	$0.12 \leq f \leq 0.24$	$12 \leq Dc \leq 12$
	$0.2 \leq d \leq 1$	$100 \leq L_w \leq 100$
	$120 \leq Ks \leq 120$	$4 \leq Zc \leq 4$
	$0.0079 \leq \rho \leq 0.0079$	$292 \leq n \leq 292$
	$372.8560 \leq W_2 \leq 375.3712$	$0.18 \leq C \leq 0.18$
	$3715.4989 \leq N \leq 4777.0701$	$0.6667 \leq Zs \leq 0.6667$

D. Experimental Work

The experiment has conducted on the VMC for authentication of the MOGA and ANN results. The experimental setup with Vertical milling Centre and KISTLER dynamometer is shown in Fig. 4. AISI1020 material and carbide end mill with 12 mm diameter has been selected as a workpiece and cutter for end milling operation. Table III indicates the chemical composition of AISI1020 material. The initial weight and final weight of workpieces have been measured and calculate the experimental values of Material removal rate. KISTLER dynamometer have been used for the measurement of tangential cutting force and torque. Dynamometer fixed on the table of milling machine and workpiece clamped on the dynamometer. The power has been determined based on experimental values of tangential cutting force. A stopwatch has been used for the measurement of machining time. The Experimental results of 25 datasets are indicated in Table IV (Appendix-A).

Fig. 4 Vertical milling Centre with KISTLER dynamometer

Table III Chemical composition of AISI1020

Elements	Mn	P	S	C	Fe
Composition in %	0.565	0.026	0.039	0.197	99.100

III. RESULTS AND DISCUSSION

In this study, AI techniques such as ANN and MOGA are used for prediction and multi objective optimization for end milling operation individually. The Predicted result of the ANN model for responses is shown in Table V (Appendix-B).

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DOI: 10.35940/ijitee.H9225.0610821
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ISSN: 2278-3075 (Online), Volume-10 Issue-8, June 2021

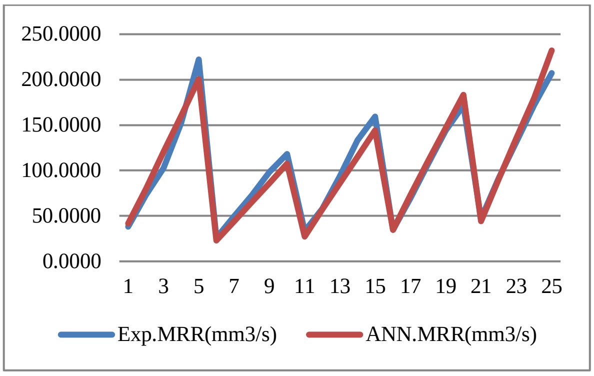

Fig. 5 Exp. Vs ANN results for MRR

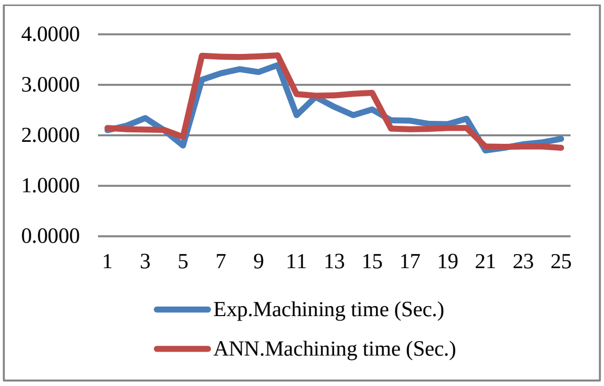

Fig. 6 Exp. Vs ANN results for machining time

The Experimental results of 25 datasets are indicated in Table IV (Appendix-A).ANN model predicted values compared with experimental results, which are shown in Fig. 5 for MRR, Fig. 6 for machining time, Fig. 7 for tool life, Fig. 8 for tangential cutting force, Fig. 9 for torque and Fig. 10 for power individually. The achieved correlation coefficient is 0.99497 among the experimental and ANN results. The values of mean percentage error are 8.017% for material removal rate, 0.106% for tool life, 7.317% for machining time, 7.329% for tangential cutting force, 7.891% for power and 9.689% for torque.

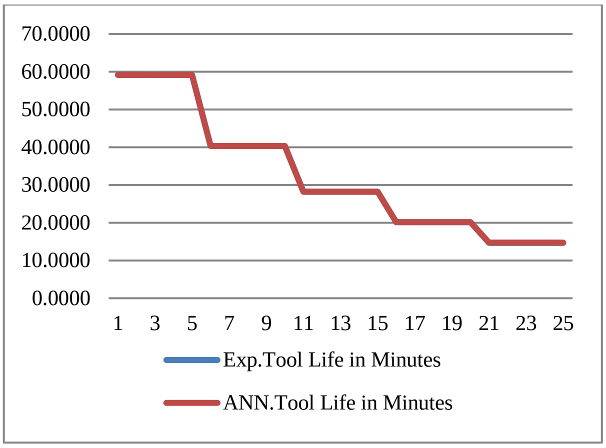

Fig. 7 Exp. Vs ANN results for tool life

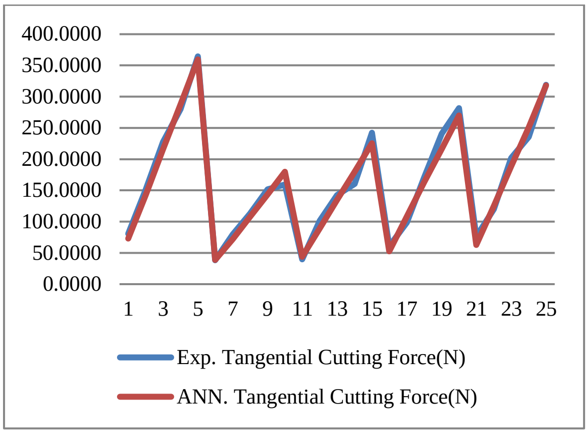

Fig. 8 Exp. Vs ANN results for tool life

It prove that an artificial neural network is capable for prediction of process parameters before experimentation. The eighteen optimum solutions with combinations of input variables are shown in Table VI (Appendix-C).

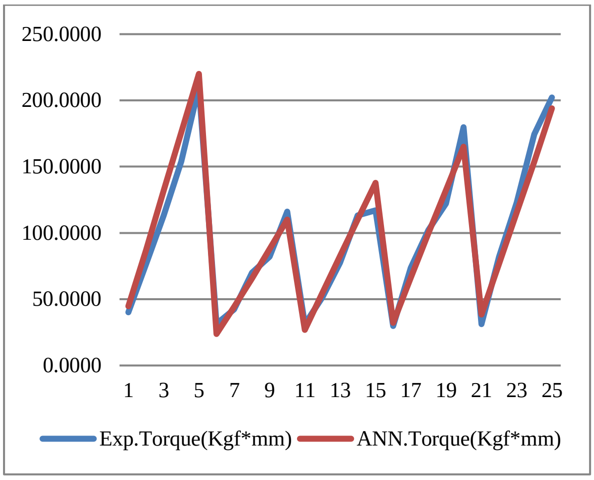

Fig. 9 Exp. Vs ANN results for torque

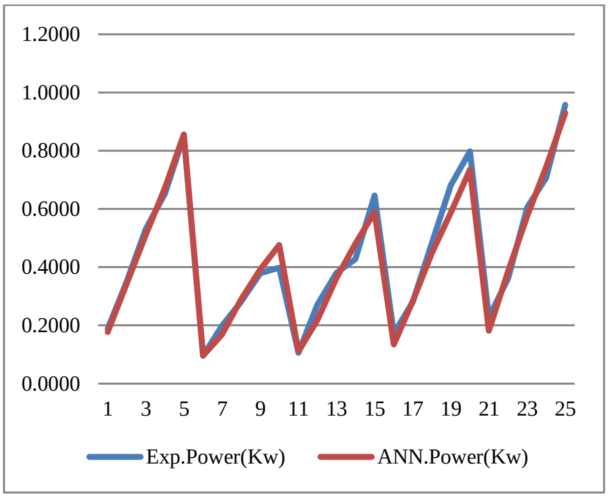

Fig. 10 Exp. Vs ANN results for power

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The minimum and maximum values of MRR is 25.3993 and 249.59, machining time is 1.56288 and 3.40099, tool life is 15.0368 and 59.3797, the tangential cutting force is 41.3341 and 341.665, torque is 25.2894 and 209.041and power is 0.0964193 and 0.945224. The Pareto optimal front distributed points shown in Fig.11 are generated from the multi objective optimization tool of selected responses. The one set of optimized cutting parameters shown in serial number 10 in table VI (Appendix-C) is given a batter result of responses so that it is validated through experimentation. It has been found the percentage of error is 3.199% for MRR, 0.347% for tool life, 13.167% for machining time, 6.260% for tangential cutting force, 6.260% for power and 0.527% for torque.

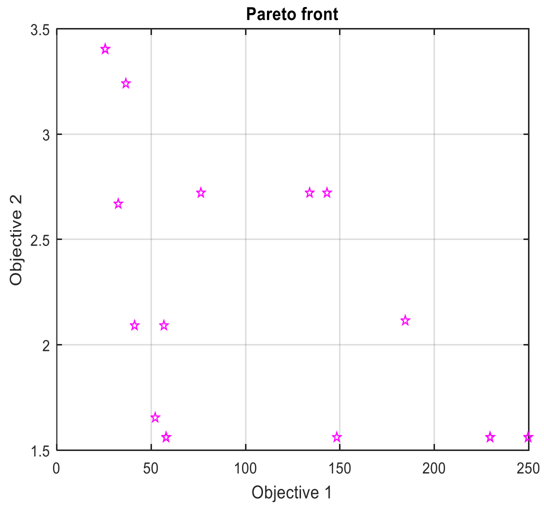

Fig. 11 Pareto optimal front chart

The experiment results indicated good agreement with multi objective genetic algorithm tool results with optimum end milling process parameters. The MOGA approach presented here gives optimum machining conditions for consequently given maximum and minimum values of responses. It has been observed that all the solution generated by MOGA is good.

IV. CONCLUSION

The AI techniques such as ANN and MOGA developed based on the mathematical model. The best cutting condition of AISI1020 has been determined for maximum MRR, tool life and Minimum machining time, tangential cutting force, torque and power. The ANN model gives average accuracy of 91.983% for material removal rate, 99.894% for tool life, 92.683% for machining time, 92.671% for tangential cutting force, 92.109% for power and 90.311% for torque. Good correspondence has been found among the ANN values with experimental results. Multi-objective genetic algorithm based Pareto optimal designs approach achieved the values of responses with maximum material removal rate is 229.331 m^3/sec, tool life is 59.343 minutes and minimum machining time is 1.563 sec, the tangential cutting force is 314.665 N, torque is 209.041 kgf. mm and power is 0.797 simultaneously in terms of cutting speed of 140.016 m/min., feed rate of 0.24 mm/tooth and depth of cut of 0.950 mm. The MOGA gives average accuracy of 96.801% for MRR, 99.653% for tool life, 86.833% for machining time, 93.74% for cutting force, 93.74% for power and 99.473% for torque. The experiment results indicated good agreement with multi objective genetic algorithm tool results with optimum end milling process parameters. This indicates that the ANN and MOGA can be fruitfully used to find the optimum combination machining variable for the end milling process. The results of this research is very useful in manufacturing industries to reduce experimental trial, cost, lead time and power consumption also improve the productivity of the product.

ACKNOWLEDGEMENT

I express my deep sense of gratitude and thanks to my supervisor Dr. Komal G Dave for her guidance, suggestions and sympathetic attitude which inspired me for this research work also thanks to the editor-in-chief of the International Journal of Innovative Technology and Exploring Engineering for providing me this opportunity to publish my work.

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APPENDIX-A

Table IV Experimental Results

Sr. no.	Cutting speed	Feed	Depth of cut	BHN	Density	MRR	Machining time	Tool life	Tangential cutting force	Torque	Power
1	140	0.24	0.2	130	7860	38.095	2.100	59.138	80.845	40.161	0.189
2	140	0.24	0.4	130	7860	73.059	2.190	59.138	150.998	76.589	0.352
3	140	0.24	0.6	130	7860	102.564	2.340	59.138	227.519	113.101	0.531
4	140	0.24	0.8	130	7860	152.381	2.100	59.138	279.907	153.889	0.653
5	140	0.24	1	130	7860	222.222	1.800	59.138	364.483	210.149	0.850
6	150	0.12	0.2	130	7860	25.806	3.100	40.324	38.259	31.367	0.096
7	150	0.12	0.4	130	7860	49.536	3.230	40.324	79.479	42.400	0.199
8	150	0.12	0.6	130	7860	72.508	3.310	40.324	112.871	70.015	0.282
9	150	0.12	0.8	130	7860	98.462	3.250	40.324	151.965	82.149	0.380
10	150	0.12	1	130	7860	117.994	3.390	40.324	159.224	116.192	0.398
11	160	0.15	0.2	130	7860	33.333	2.400	28.184	39.745	31.257	0.106
12	160	0.15	0.4	130	7860	57.971	2.760	28.184	101.411	51.389	0.270
13	160	0.15	0.6	130	7860	93.750	2.560	28.184	142.548	77.528	0.380
14	160	0.15	0.8	130	7860	133.333	2.400	28.184	160.447	113.101	0.428
15	160	0.15	1	130	7860	159.363	2.510	28.184	242.447	117.128	0.646
16	170	0.18	0.2	130	7860	34.783	2.300	20.132	60.634	29.794	0.172
17	170	0.18	0.4	130	7860	69.869	2.290	20.132	98.706	73.547	0.280
18	170	0.18	0.6	130	7860	107.623	2.230	20.132	170.483	102.111	0.483
19	170	0.18	0.8	130	7860	144.144	2.220	20.132	240.658	122.153	0.682
20	170	0.18	1	130	7860	171.674	2.330	20.132	281.519	179.731	0.797
21	180	0.21	0.2	130	7860	47.059	1.700	14.659	76.044	31.273	0.228
22	180	0.21	0.4	130	7860	91.429	1.750	14.659	120.224	82.052	0.361
23	180	0.21	0.6	130	7860	131.868	1.820	14.659	202.116	122.913	0.606
24	180	0.21	0.8	130	7860	172.043	1.860	14.659	235.598	174.578	0.707
25	180	0.21	1	130	7860	207.254	1.930	14.659	319.259	202.186	0.958

Retrieval Number: 100.1/ijitee.H92250610821
DOI: 10.35940/ijitee.H9225.0610821
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication

International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-10 Issue-8, June 2021

APPENDIX-B

Table V ANN model results

Sr. no.	Cutting speed	Feed	Depth of cut	BHN	Density	MRR	Machining time	Tool life	Tangential cutting force	Torque	Power
1	140	0.24	0.2	130	7860	41.755	2.147	59.105	72.895	44.608	0.177
2	140	0.24	0.4	130	7860	79.795	2.121	59.105	142.493	87.186	0.346
3	140	0.24	0.6	130	7860	120.444	2.116	59.105	215.868	132.075	0.511
4	140	0.24	0.8	130	7860	159.909	2.108	59.105	287.581	175.940	0.673
5	140	0.24	1	130	7860	200.580	1.970	59.105	359.629	220.032	0.856
6	150	0.12	0.2	130	7860	22.933	3.576	40.312	38.826	23.757	0.096
7	150	0.12	0.4	130	7860	43.678	3.554	40.324	72.203	44.177	0.168
8	150	0.12	0.6	130	7860	64.979	3.549	40.319	107.571	65.805	0.289
9	150	0.12	0.8	130	7860	85.929	3.565	40.303	143.554	87.817	0.393
10	150	0.12	1	130	7860	107.559	3.583	40.288	180.077	110.170	0.476
11	160	0.15	0.2	130	7860	27.392	2.817	28.189	44.000	26.924	0.110
12	160	0.15	0.4	130	7860	57.111	2.785	28.198	89.536	54.779	0.218
13	160	0.15	0.6	130	7860	86.191	2.790	28.194	134.931	82.543	0.363
14	160	0.15	0.8	130	7860	115.069	2.820	28.185	180.005	110.126	0.481
15	160	0.15	1	130	7860	144.149	2.842	28.178	225.199	137.790	0.590
16	170	0.18	0.2	130	7860	34.777	2.133	20.129	52.493	32.121	0.135
17	170	0.18	0.4	130	7860	73.288	2.119	20.131	108.194	66.194	0.283
18	170	0.18	0.6	130	7860	110.676	2.129	20.127	162.804	99.605	0.449
19	170	0.18	0.8	130	7860	147.170	2.147	20.122	216.077	132.213	0.587
20	170	0.18	1	130	7860	183.474	2.145	20.120	269.849	165.120	0.736
21	180	0.21	0.2	130	7860	44.083	1.777	14.715	62.624	38.319	0.182
22	180	0.21	0.4	130	7860	90.285	1.773	14.715	125.392	76.718	0.385
23	180	0.21	0.6	130	7860	135.999	1.779	14.715	188.603	115.403	0.576
24	180	0.21	0.8	130	7860	179.833	1.780	14.715	251.099	153.649	0.744
25	180	0.21	1	130	7860	232.151	1.752	14.715	317.942	194.107	0.930

Retrieval Number: 100.1/ijitee.H92250610821
DOI: 10.35940/ijitee.H9225.0610821
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication

APPENDIX-C

Table VI Non dominated pareto optimal solution

Sr. no.	Cutting speed	Feed	Depth of cut	BHN	Density	MRR	Machining time	Tool life	Tangential cutting force	Torque	Power
1	178.38	0.138	0.2	120	7860	134.211	2.721	15.456	41.334	25.289	0.123
2	140	0.138	0.2	120	7860	76.089	2.72	59.38	41.334	25.289	0.096
3	167.188	0.139	0.92	120	7860	25.399	3.401	22.153	192.278	117.641	0.536
4	179.265	0.24	0.216	120	7860	57.771	1.564	15.037	77.549	47.447	0.232
5	179.265	0.227	0.92	120	7860	41.325	2.09	15.037	312.842	191.406	0.934
6	179.265	0.24	0.67	120	7860	249.579	1.563	15.037	240.979	147.438	0.72
7	155.439	0.178	0.204	120	7860	184.585	2.113	33.208	54.237	33.184	0.14
8	179.265	0.227	0.931	120	7860	52.228	1.654	15.037	316.455	193.617	0.945
9	155.439	0.146	0.95	120	7860	36.392	3.243	33.208	208.202	127.384	0.539
10	**140.016**	**0.24**	**0.95**	**120**	**7860**	**229.331**	**1.563**	**59.343**	**341.665**	**209.041**	**0.797**
11	149.204	0.178	0.763	120	7860	32.329	2.672	41.689	202.817	124.089	0.504
12	140.063	0.24	0.216	120	7860	148.134	1.564	59.233	77.549	47.447	0.181
13	149.204	0.24	0.204	120	7860	249.579	1.563	41.689	73.334	44.868	0.182
14	140	0.24	0.42	120	7860	229.331	1.563	59.38	151.067	92.428	0.352
15	140	0.138	0.2	120	7860	143.42	2.72	59.38	41.334	25.289	0.096
16	179.265	0.24	0.216	120	7860	57.771	1.564	15.037	77.549	47.447	0.232
17	179.265	0.227	0.795	120	7860	56.465	2.09	15.037	270.338	165.401	0.807
18	167.188	0.139	0.92	120	7860	25.399	3.401	22.153	192.278	117.641	0.536

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DOI: 10.35940/ijitee.H9225.0610821
Journal Website: www.ijitee.org

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